THREE ESSAYS ON THE GROWTH OF THE MARKET FOR PATENTS AND ITS CHALLENGES TO INNOVATION POLICY

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THREE ESSAYS ON THE GROWTH OF THE MARKET FOR PATENTS AND ITS CHALLENGES TO INNOVATION POLICY

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Is the market for patents a mere part of the market for technology? In my dissertation, I showed that although some instances of patent ownership transfer may be a part of technology transfer, not all patent transfers are so.

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SUMMARY

A sheer number of US patents have been transferred through market transactions and that the size of the market for patents has grown.

In this dissertation, I conduct three complementary studies to examine how the market for patents shapes technological innovation. Drawing on the broad discussion of the benefits and costs of patent ownership transfer for invention, I develop three research questions, and in three essays I address each of them through building theoretical models and conducting empirical analysis.

In the first study, I examine a firm's economic incentive for purchasing patents to gain strategic benefit over market rivals and how the firm's patents purchase results in the market rival's innovative activities. In the second study, I investigate the antitrust issue of patent consolidation caused by the purchase of multiple patents by a small number of firms and the impact of a governmental authorities' regulation of the generated patent monopolies by patent consolidation on the development of follow-on innovations. In the last study, I analyze the impact of granting a firm the exclusive access to a university's inventions through patents transfer on the follow-on innovative activities.

Altogether, this dissertation contributes to advancing our understanding of the distinctive nature of the market for patents from the market for technology, and it extends the conventional discussion of how the patents system may affect innovation.

CHAPTER 1
INTRODUCTION

1.1 Presence and Growth of the Market for Patents

A patent codifies a novel, useful, and non-obvious (35 U.S.C. 101) idea into a legal document and confers a temporal exclusive right to use it, becoming transferable property (35 U.S.C. 261). In other words, one can sell or purchase ownership of a patent.

Patent transfer through market transaction forms the market for patents. Because patent-associated transactions are often subject to substantial transaction costs (Gambardella, 2005; Lemley and Myhrvold, 2007; Troy and Werle, 2008; Benassi and Di Minin, 2009), one might expect the market for patents to be an inefficient market. Unlike products in typical markets, each patent is unique, and thus there is usually a limited number of potential buyers for each patent seller. Also, because one cannot know the actual value of a patent (Lemley and Myhrvold, 2007), not only because of the difficulty in evaluating the quality of patent itself but also because of the challenges in estimating the economic contribution of the patented technology as it used to be the "input" for other innovation (Griliches, 1990). This uncertainty creates information asymmetry between the buyer and seller of a patent. Often, this information asymmetry makes the patent market inefficient. Accordingly, one may assume the market for patents is not that active nor sizable.

Surprisingly, a series of recent studies find that the patent market is active. Serrano (2010) found that the ownership of 13.5% of US patents has changed at least once during the patent life. Serrano and Ziedonis (2018) revealed that about 70% of the patents owned by failed startups are redeployed through patent ownership transfer. Meanwhile, about one out of three European Patent Office (EPO) patents have been transferred at some time (Ciaramella et al., 2017).

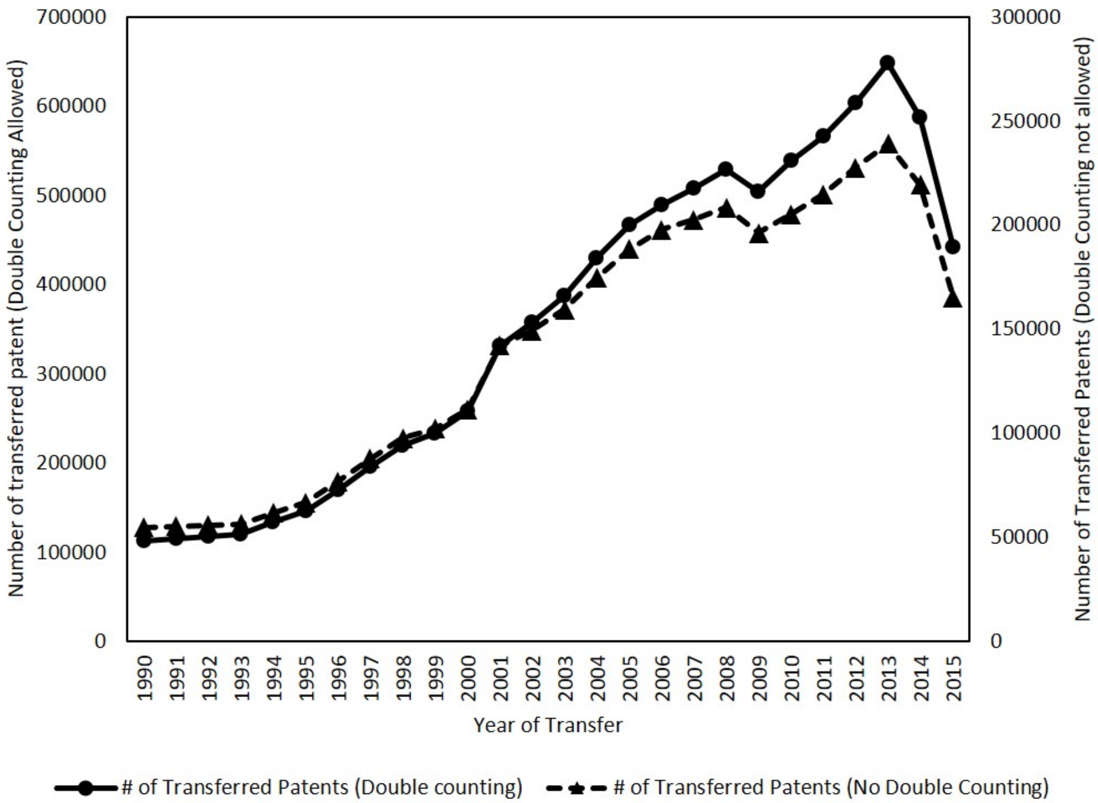


Figure 1.1: Number of Transferred US Patents by Year

Aside from the presence of a active market for patents, my calculation of the number of US patents that were transferred through market transaction[1] using the USPTO patent assignment databases (Graham et al., 2018) shows extensive growth of the market for patents in the US. As shown in Figure 1.1, the number of traded patents grew from 112,326 in 1990 to 442,002 in 2015.[2]

One may explain the growth of the market for patents as the result of business activities that often accompany patents transfer, such as mergers and acquisition (M&A). However, the trends of the M&A transaction volume and value both at the worldwide (Figure 1.3)

1 Excluding patent transfer before the patent application exists, cases in which the patent owner's name changed, correction for the reason of patents reassignment, secularization of patents by patents collateral, and patents transfer between corporate-hired inventors and employers.

2 The pattern of decrease in the number of transferred patents seen in 2014 is due to the delay between patent application and publication as well as the delay in indexing patent transfer records in the database. The substantial drop actually occurred around 2008, probably because of the global financial crisis and the bankruptcy of Lehman Brothers.

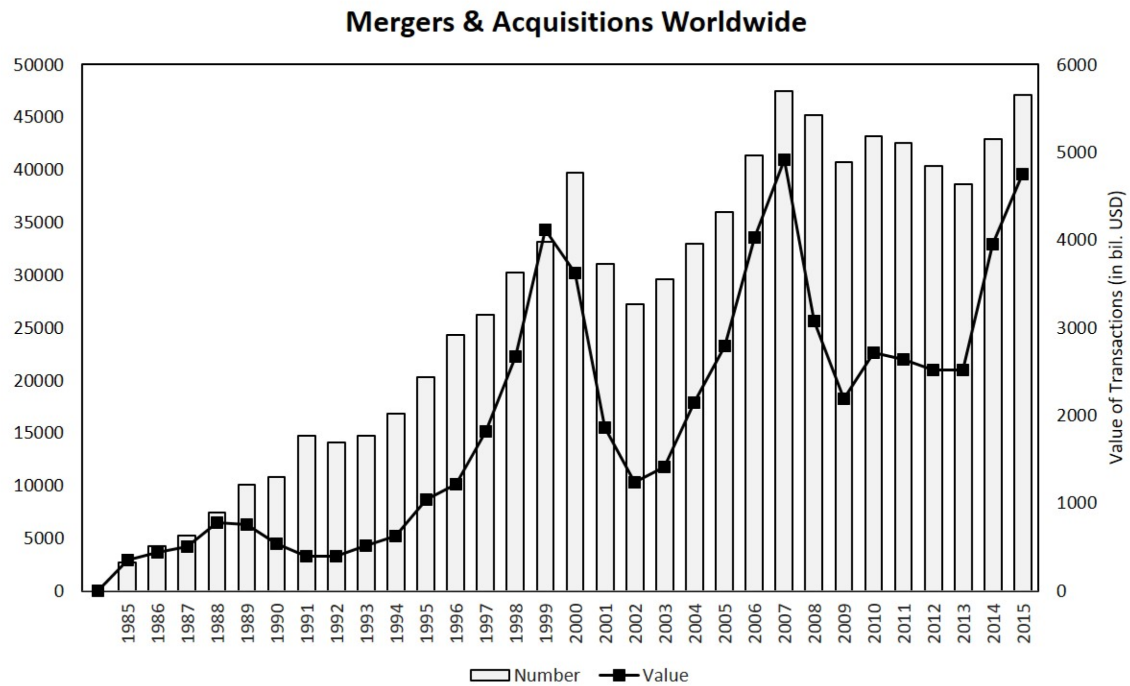


Figure 1.2: M&A Transaction by Year (World Wide)

and national scales (Figure 1.2) seem not to correlate with the pattern of ever-increasing numbers of transferred US patents.

It can also be argued that the increase seen in the last three decades is simply due to increasingly accumulated patents available for transfer. However, my estimation of the patent transfer propensity[3] presented in Figure 1.4 still shows a growing pattern over the period from 1990 to 2015.

1.2 Market for Patents and Innovation

The presence of a sizable market for patents draws the attention of innovation management scholars and policymakers regarding how the market for patent transfer shapes technological innovation (hereafter, Innovation). Given that the patent is one of the primary institutional devices for incentivizing innovation yet can cause undesirable consequences for innovation, patent transfer can have both beneficial and costly effects on innovation as

[3] The denominator is the number of active US patents available for transfer in the year observed.

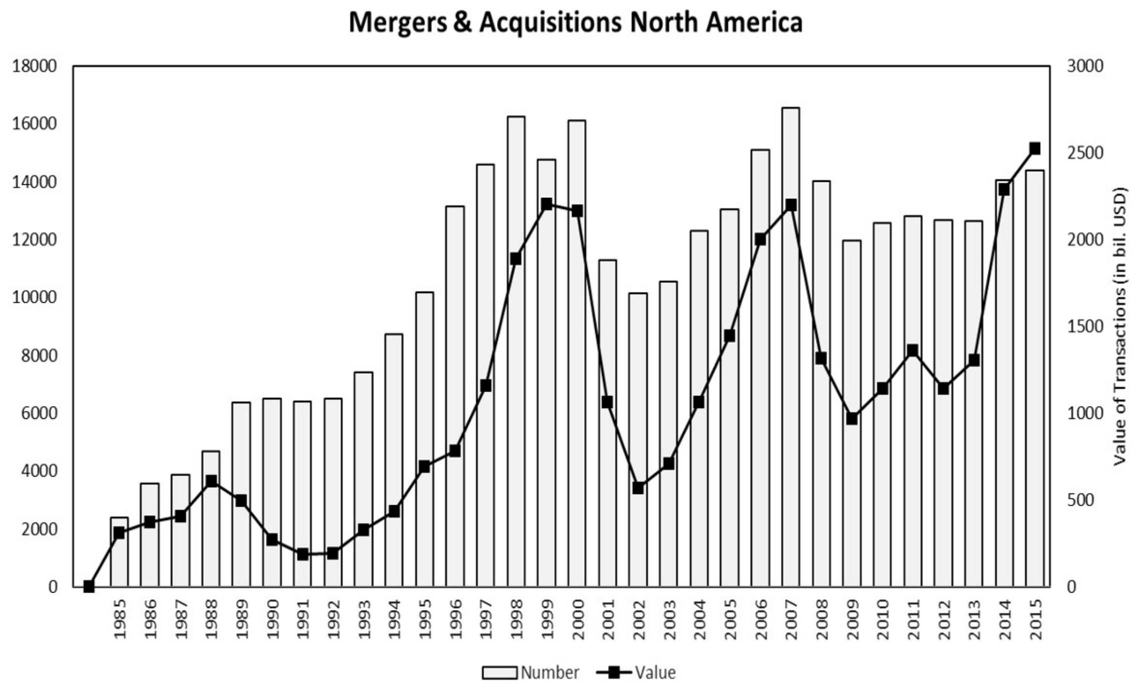


Figure 1.3: M&A Transaction by Year (in U.S.)

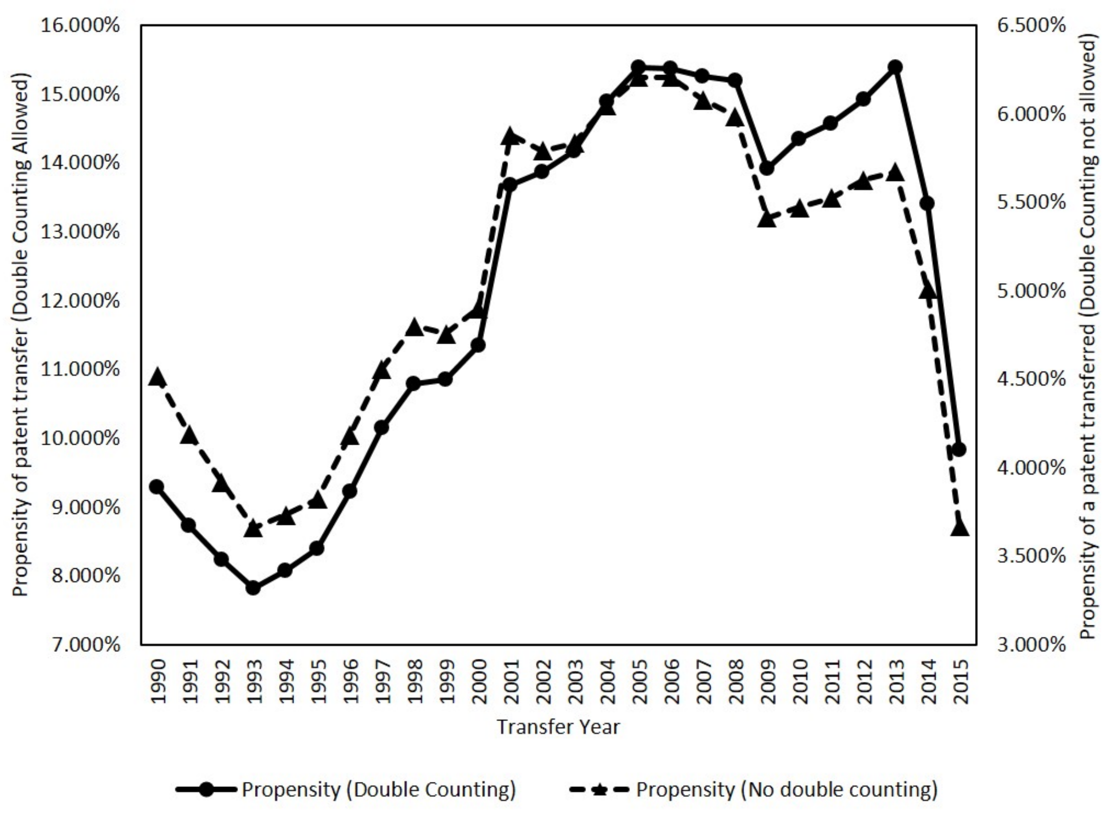


Figure 1.4: Propensity of patent Transfer by Year

well. Indeed, there is an on-going relevant discussion of the conflicting consequences of patents transfer on innovation.

On the one hand, an active patent market can promote innovation. First, the patent market provides more opportunities for inventors to reap economic benefits from their innovative activities (Arora, 1997; Gambardella, 2005; Galasso et al., 2013; Odasso et al., 2014; Spulber, 2015). The more active the market for patents, the greater the chance of selling a patent and the greater the inventor's expected revenues from that invention, which creates economic incentive for future innovative activities (Kremer, 1998). This benefit may be particularly prominent for individuals or start-ups that are financially constrained in conducting R&D (Hall, 2002) and commercializing their innovations (Ferrill, 2004; Gambardella et al., 2007). Given that directly profiting from invention through commercialization of patent is risky and costly, transferring patents could be a more convenient and less risky way for inventors to benefit financially from their inventions.

Second, as the patent system is a crucial institution that enhances technology transaction efficiency (Shane, 2002; Gans et al., 2008; Arora and Gambardella, 2010; Cockburn et al., 2010; Gans and Stern, 2010; Spulber, 2015) and transferring patent ownership can be an alternative way of transferring technology (Jeong et al., 2013), encouraging patent transfer is one way of promoting technology transfer and, therefore, improving the efficiency of the innovation process through invigorating the division of innovative labor, as the literature on the market for technology explains (Arora, 1997; Arora et al., 2004, 2013). Several empirical studies support this idea.

Burhop (2010) shows that the patent market facilitates technology transfer and promote knowledge spillover. By analyzing the characteristics of patents that were traded in the late 19th to early 20th century in Germany, this study suggests that the active patent market in 19th century Germany contributed to the country's industrialization. A study by Tsai and Wang (2008) shows that firms' inward patent licensing and patent purchasing activities have positive relationships with its performance if the firm has sufficient absorptive capacity. The study concludes that externally acquired patents can complement firms' internal R&D capabilities. Akcigit et al. (2016) show that patent transactions not only help to correct the misallocation of ideas across firms ex-post facto but also influence firms' growth while encouraging their R&D. The authors argue that the patents market allows firms to reorganize their patent portfolio, which enables them to manage their IPR assets better and to make a more efficient R&D investments, thereof. In their study, Jeong et al. (2013) show that patent trading may be complementary to patent licensing, which supports the idea that patent ownership transfer can be another channel for technology transactions.

Third, patent transfer reallocates existing patents so that these patents can be used more effectively. For example, the market for patents can reduce the cost incurred by patent infringement disputes by reallocating the patents to those who are better equipped to enforce patents right. Galasso et al. (2013) and Haus and Juranek (2018) provide evidence supporting this idea by showing that the transfer of patents to those who have stronger capabilities in patents enforcement than the original patentee reduces the delay in settling patent infringement disputes. This finding implies that patents transfer could encourage the division of labor between developing and protecting the invention, which would contribute to improving the overall efficiency of the innovation process. Patents transfer, in this case, is expected to improve patents' enforceability as well as inventors' appropriability.

On the other hand, patent transfer can deter innovation. The fact that patents are used for strategic purposes through patents enforcement (e.g., Cohen et al., 2000; Ziedonis, 2004; Motohashi, 2008; Graham et al., 2009) or that firms have incentive to preempt patents to maintain stronger downstream market power (Gilbert and Newbery, 1982; Gilbert, 1987) is at the center of this thought: some firms purchase patents solely in order to exploit the patent exclusion rights to gain strategic benefits over their market competitors. A study of Kelley (2011) suggests that growth of patent transfers are probably driven by entities that seek benefits from the strategic use of patents. Based on the interviews with patent intermediaries and technology firms in Silicon Valley, this study concludes that patent transfer could be trading of intellectual weapons between firms. The patents transfer for strategic use can impose the following undesirable effects.

First, it can aggravate the ex-post patent holdup issue or promote frivolous patents infringement disputes, which drives up the cost of innovation. For example, firms may purchase patents to build barriers preventing the entry of potential market competitors or to impose greater operating costs on present market competitors (Hahn, 1984; Morton and Shapiro, 2013) to have a strategic advantage in downstream market competition. As a result, a downstream innovator could be faced with a greater cost to innovate, which would divert resources from efficient R&D investments. Because patents can also be used as bargaining chips for settling patents infringement disputes (Hall and Ziedonis, 2001; Ziedonis, 2004; Thumm, 2004), firms could be motivated to purchase others' patents for pure defensive purpose rather than to commercialize the underlying inventions. Such patent aggregation for pure strategic benefit could prevent the genuine technology transfer that might otherwise happen (e.g., Kwon and Motohashi, 2014).

This concern becomes even more salient with the emergence of Patent Assertion Entities (PAEs), which are defined as business entities that purchase patents for the sole purpose of leveraging the risk of firms that are under litigation for patent infringement. Some argue that PAEs may promote innovation by stimulating the market for technology and brokering patents transfer (McDonough III, 2006; Shrestha, 2010). However, because these entities typically seek to extract excessive fees from operating firms through ex-post patent assertion, other scholars argue that PAEs do not contribute to the market for technology but generate unnecessary social cost (Fischer and Henkel, 2012; Kwon and Motohashi, 2014; Caviggioli and Ughetto, 2016).

A patent transaction that could increase the ex-post patent holdup risk has recently become one of the stated concern of innovation policymakers (FTC, 2011). According to policy discourse, ex-post patent transactions do not contribute to innovation because they increase product prices while failing to improve consumer welfare.

Second, patent transfer practices can raise antitrust issues. The patent market enables consolidation of existing patents by a few firms, which could discourage downstream market competition by effectively forming a monopoly on upstream technology as well as the relevant downstream markets. For example, if a firm purchases all the existing patents on a particular technology that is essential for making a product, the patent-acquiring firm can effectively secure excessive market power allowing it to monopolize the corresponding downstream product market (See Hahn, 1984). Regarding this concern, a study by Figueroa and Serrano (2013) shows that there is no evidence of a concentration of patents to few firms when it comes to patent trading between small and large firms. Yet, the aggregation of patents by few firms remains one of the antitrust regulatory authority's concerns in the U.S. Indeed, patent transactions that result in the creation of a monopoly has been the subject of regulatory review (Brown and Zun, 2011; Gotts and Sher, 2012) by the antitrust division of the US Department of Justice and the Federal Trade Commission (FTC).

A few firms' monopolization of upstream technology through patents consolidations could discourage innovation in the sectors where cumulative innovation is pervasive and critical. If a firm monopolizes ownership of existing patents, other firms' access to the necessary technology for developing the follow-on innovation could be substantially restricted.

Third, patent transfer can deter scientific progress and follow-on research. This is of particular concern in relation to the transfer of universities' patented inventions in scientific commons to private firms. Universities often use public research funds to conduct basic scientific research, which can be the foundation for technological innovation. When the resulting inventions on outcomes of such scientific research are privatized through transfer of the patents to firms, access to the underlying scientific knowledge could be excessively restricted, as demonstrated by the story of the exclusive licensing of the OncoMouse patents to DuPont by the University of California (Murray, 2006). The restricted accessibility to the scientific commons can impede and delay follow-on scientific research as well as the follow-on innovation (Partha and David, 1994; Argyres and Liebeskind, 1998; Heller and

Eisenberg, 1998; Nelson, 2004; Walsh et al., 2007).

1.3 Research Questions & Overview

Motivated by the discussion summarized above, the aim of this dissertation is to elucidate the nature of the market for patents through exploration of how patent transfer shapes innovation by examining the effect of patent transfer on development of relevant inventions to the transferred patent. I conduct three complementary studies to explore how patent transfers that the three key actors in the system of innovation involves in affect the development of relevant inventions: firms (Essay 1), governments (Essay 2), and universities (Essay 3).

Essay 1. Impact of Patent Ownership Transfer on Patent Holdup Risk and Innovation of Firms

In the first essay, I examine whether firms have economic incentive to purchase others' patents to use those patents for strategic benefits over market rivals. To this end, I start by constructing an analytical model to investigate whether the exploitation of a rival firm's patent holdup risk is an incentivizing benefit for a firm to purchase a patent. The model demonstrates that a firm has a strong economic incentive to purchase the patent that is crucial for the rival firm's market operation because doing so allows the patent-purchasing firm to leverage the rival's patent holdup risk, thus benefiting in market competition.

The extended model that incorporates the firm's production function and patented technology as an input for the production derives a hypothesis stating that a firm's patent purchase will make the rival firm less active in developing technologies relevant to the purchased patent if the patent is critical to the rival firm's operations. I empirically test this hypothesis by analyzing the case of the Nortel patent auction in the US in 2011.

Essay 2. How Does Antitrust Regulation of Patents Consolidation Affect Follow-on Innovation?

In the second essay, I examine how governmental regulation of formation of patent monopolies through the prevention of patent consolidation by a firm affects the development of follow-on innovation.

I start by building a three-firm model to explore how a firm's patents consolidation configures the market competition and development of follow-on innovation. The model predicts that a firm's consolidation of existing patents on substitutes for the patented upstream technology that it already owns deters follow-on innovation of its market competitors while not creating incentive for the patent consolidating firm to develop additional follow-on invention. In this case, antitrust regulation of the firm's patents consolidation is expected to mitigate its negative effect on the market competitors' follow-on innovation. I test this prediction by using the case of the US Department of Justice's (DoJ) partial regulation of patents transfer from Novell to Microsoft, Oracle, EMC, and Apple in 2011.

Essay 3. Granting a Firm the Exclusive Access to a University's Inventions and Its Effect on Follow-on Innovation

The third essay examines the impact of conferring exclusive access to a university's inventions to outside firms on the rate of follow-on invention. This study focuses on examining how granting a firm the exclusive right to use a university's inventions distinctively affects the follow-on innovative activities by entities (i.e., recipients vs. non-recipients of the exclusive access) and the nature of patented idea (scientific commons vs. those that are not).

As an empirical strategy, I consider patent ownership transfer from a university to a firm as a way of conferring an exclusive right to use the university's invention, while defining the scientific commons as an invention created based on federal research funding or a patent that has a tight link to the scientific knowledge originated from federally sponsored research. My data consists of US patents that were transferred by 107 US research-intensive universities to various firms from 2000 to 2013.

1.4 Structure of this Dissertation

This dissertation is structured as follow. Essays 1, 2 and 3 are presented in Chapters 2, 3, and 4, respectively. Each chapter consists of an introduction, theoretical model or literature review, empirical setting, results, and conclusions. Chapter 5 concludes the dissertation with a discussion of the implications for innovation policy makers and the scholarly contributions.

CHAPTER 2

IMPACT OF PATENT OWNERSHIP TRANSFER ON PATENT HOLDUP RISK AND INNOVATION OF FIRMS

The growth of the market for patents has drawn the attention of innovation management scholars and policymakers to the impact this market may have on innovation. One of their prominent questions is whether firms exploit the market for patents to obtain strategic benefits over their market rivals, which may aggravate ex-post patent holdup and increase the cost of innovation.

In this study, I examine how a firm's patent purchase affects its rival's innovative activity when the patent can be strategically utilized by the patent purchasing firm against its rival. I investigate whether there is an economic incentive for the firm to purchase a patent to strategically utilize the patent against the market rival. Then, I derive a hypothesis stating that the firm's patent purchase deters the rival firm's development of relevant technologies to that patent if the patent covers crucial technological input for the rival's market operation, by imposing a greater patent holdup risk to the rival firm.

My analysis using Nortel's patent auction case in 2011 finds supportive evidence for the short term effect. Finally, I discuss the different nature of the market for patents from the market for technology and how we must understand these differences to formulate better innovation policies.

2.1 Introduction

Although a great number of patents have been transferred through market transactions, and studies have repeatedly shown the presence of a sizable market for patents in the United States, how patent ownership transfer may affect innovation has been less explored. On the one hand, when patent ownership is transferred to those who can enforce the patents better than the original patent owner, the patent transfer reduces unnecessary patent infringement lawsuits and associated costs (Galasso et al., 2013) while it compensates inventors for underutilized inventions (Kremer, 1998; Ferrill, 2004).

Transacting title to a patent is a way of transferring technology (Arora, 1997; Arora and Fosfuri, 2003; Arora and Gambardella, 2010; Jeong et al., 2013). The technology market enhances the efficiency of the innovation process by promoting the division of innovative labor and diffusion of technology (Arora, 1997; Arora and Fosfuri, 2003; Arora et al., 2004, 2013).

On the other hand, firms may trade patents for the strategic exploitation of the patent exclusion right without having the intention to market the patented technology. As many studies show, firms use patents as a defensive bargaining chip for settling patent infringement disputes (Hall and Ziedonis, 2001; Thumm, 2004; Ziedonis, 2004) or for deterring a competitor's market entry (Cohen et al., 2000; Motohashi, 2008; Graham et al., 2009). Hence, patent ownership transfer is not necessarily a result of technology transactions (See, Monk, 2009; Kelley, 2011; Figueroa and Serrano, 2013; Galasso et al., 2013; Morton and Shapiro, 2014) but may, instead, be part of a firm's intellectual property strategy.

So, how does a patent transfer for the strategic use of patent exclusion rights affect a firm's innovative activity? The literature on patent holdup and firms' defensive use of patents both hint at the answer: It depends on which firm acquires a patent and whether the firm is at risk of a patent holdup with regard to the patent of interest. When patents are acquired by a rival firm that has stakes in the opportunistic use of patents against the focal firm, the focal firm is likely to suffer from an increased patent holdup risk. The patent holdup hypothesis asserts that once a firm is exposed to a greater level of patent holdup risk, the firm will produce less and make inefficient R&D investments (Lemley and Shapiro, 2006; Galetovic et al., 2015). On the other hand, a firm's preemptive patent purchase immunizes the firm to the probable patent holdup that would occur if the patent was purchased by another firm. Such defensive patent purchase strategies are a foundation of the business of defensive patent aggregators (Hagiu and Yoffie, 2013; Cosandier et al., 2014; Morton and Shapiro, 2014; Kwon and Drev, 2017).

Although the reasoning outlined above appears to offer a straightforward understanding of the patent market and how it relates to firms' innovative activities, there are surprisingly few studies in this regard. The literature on the strategic use of patents has focused on theorizing how firms leverage the patent holdup risk of their rivals, while some empirical studies have found evidence of the detrimental impact to innovation of opportunistic exploitation of patent holdup risk (Walsh et al., 2003; Cockburn and MacGarvie, 2009; Elhauge, 2008; Galetovic et al., 2015). Meanwhile, a study on the patent market by Graham et al. (2018) examined the development of the market in the United States, and Ciaramella et al. (2017) examined its development in Europe. Serrano (2005, 2010) analyzed firms' patent trading patterns in the United States, and Galasso et al. (2013) investigated how patent transfer improves patent enforcement efficiency. Figueroa and Serrano (2013) studied the patent transaction flow between small and large firms. Kelley (2011) and Morton and Shapiro (2014) analyzed various drivers of patent transfers, and Serrano and Ziedonis (2018) examined the redeployment of the patent assets of failed start-ups. The lack of studies becomes particularly salient when considering the recent policy discourse on the necessity of legislative regulation of entities that purchase patents for the opportunistic use of patent exclusion rights against manufacturers (i.e., patent assertion entities) (FTC, 2011).

What is the nature of the strategic benefits that a firm can gain over its rival from the acquisition of external patents? How does a firm's patent purchase affect the innovative activities of its rivals?

This study explores the theoretical and empirical answers to these questions. First, by constructing a simple analytical model, I show that there is an economic incentive for a firm to purchase patents that could be critical for a rival firm's market operations in order to strategically exploit the patent holdup risk the rival firm would face. Second, by elaborating on the patent holdup theory, I expand the analytical model to illustrate how a firm's purchase of such patents may impact a rival firm's innovative activity. The model predicts that a firm's patent purchase can make the rival deter developing technologies related to the patent if the patent is crucial for the rival's market operations.

I empirically tested the derived hypothesis using the case of Nortel's patent auction (a bankrupted Canadian telecommunications equipment company).

There are three findings in this paper. First, this study showed that, theoretically, a firm can significantly enhance its profits when it leverages the patent's holdup risk for its market competitors. This benefit becomes an economic incentive for the focal firm to purchase patents that could be crucial for a rival firm's market operations.

Second, if a firm's patent purchase imposes a greater patent holdup risk on its rival, the rival becomes less active in developing technologies relevant to the patent. The patent holdup theory explains this finding.

Third, the observed impact on the rival firm, however, disappears over time. I explain this finding with the strategic actions taken by firms to mitigate (future) patent holdup risk, which was conceptualized as the "working solution" by Walsh et al. (2003).

The remainder of this paper is structured as follows. In Section 2, I review the patent holdup literature, focusing on how it increases the cost of innovation. In Section 3, by constructing an analytical model that captures the relationship between patent transfer and a firm's market competition, I explain how the benefits from strategic exploitation of a patent's holdup risk to a rival firm can incentivize a firm's patent purchase. By incorporating the patent holdup theory into the model, I rationalize how a firm's patent purchase increases the patent holdup risk of its rival and influences the rival's innovative activity thereafter. In Section 4, I describe the data and my empirical research design. Section 5 presents the findings, and in Section 6, I discuss their implications. Section 7 concludes by suggesting avenues for future research in this area.

2.2 Patent Holdup and Innovation

A patent holdup is likely to occur when the following three elements are intertwined: an essential input to a firm's production is owned by other firms; the focal firm has an asset-specific investment in that input; and the input's owner behaves opportunistically.

For example, suppose that firm A makes a product, and firm B owns an input for firm A's production. Firm A may have contracted with firm B for the use of the input in production. Firm A makes the input-specific investment, which becomes a sunk cost if firm B no longer supplies the input. By leveraging this risk, firm B may initiate an ex-post negotiation after firm A makes the input-specific investment and product, which forces firm A to pay firm B rent that is higher than the ex-ante rent to continue using the input. Expecting this situation, firm A becomes reluctant to invest in acquiring assets that have specificity to the input. In an extreme case, firm A's production can break down.

This holdup situation can happen through ex-post patent enforcement. Because a patent grants the owner the legal right to exclude others from using the patented invention, the owner can leverage the patent holdup risk to extract an excessive rent from firms that use the patented technology for their production. These firms become more vulnerable to an ex-post patent holdup if they have invested in assets that have specificity to that patent (Lemley and Shapiro, 2006; Shapiro, 2010).

The leveraging of this ex-post patent holdup risk has been blamed for discouraging innovation because firms that are exposed to the holdup will be reluctant to make optimal R&D investments (Bessen, 2004). Even more seriously, given the cumulative nature of modern innovation (Scotchmer, 2004), patent holdups can limit innovators' access to essential technologies for creating follow-on innovation. This undesirable consequence could be particularly acute in complex technology fields (Shapiro, 2010) or where standard-essential patents (SEPs) are crucial inputs for production (Farrell et al., 2007; Miller, 2007; Galetovic et al., 2015). Other theoretical studies raise similar concerns using different terms to refer to patent holdup, such as the tragedy of the anticommons and the patent thicket, which emphasize the detrimental impact of patent ownership fragmentation and the accompanying excessive cost of using patented technologies for innovation.

According to Heller and Eisenberg (1998), the tragedy of the anticommons can emerge when multiple owners each have a right to exclude others from a scarce resource, and no one has an effective privilege of use (p. 698). In this situation, the cost of acquiring the necessary patented technology for production can easily exceed the genuine value of the product while also increasing incidents of patent infringement. A similar concern was raised by Shapiro (2010) with the concept of the patent thicket, which is defined as a dense web of overlapping intellectual property rights that a company must hack its way through to commercialize new technology (p. 120). As the patent thicket that a company faces becomes denser, the cost to clear the patent thicket increases, which restricts follow-on innovation.

Interestingly, empirical studies report mixed findings on the detrimental effects to innovation of patent holdup. Walsh et al. (2003) investigated whether patent holdups hamper R&D in the biomedical industry. Surprisingly, the study did not find evidence in support of the tragedy of the anticommons hypothesis. Instead, it suggested that firms equip themselves to cope with patent holdups. A study by Galetovic et al. (2015) examined whether R&D activities in sectors where SEPs are crucial are negatively impacted by patent holdups. Their study showed no empirical evidence that SEP holdup negatively impacted overall R&D activity.

In contrast, a study by Cockburn and MacGarvie (2009) found empirical evidence showing that patent thickets impose difficulties on start-up operations. Their analysis demonstrated that start-ups in sectors where dense patent thickets exist experience a greater delay in acquiring venture capital funding than firms in sectors with less dense patent thickets. Their study also showed that start-ups in sectors with a dense patent thicket are less likely to have initial public offerings than those in sectors without patent thickets.

A subsequent study by Cockburn et al. (2010) that used survey data regarding the innovative activities of German firms showed that the relationship between a firm's innovation performance and the patent thicket depends on the firm's patent licensing activity. Specifically, they found that the innovation performance of firms was negatively correlated with the denseness of the patent thicket when firms were engaging in in-licensing activity. However, the relationship was positive for firms that did not practice in-licensing.

The mixed findings summarized above are partly explained by the ways firms cope with patent thickets or patent holdups. As Walsh et al. (2003) explained, when entities develop strategies to cope with probable patent holdup problems, they can, to some extent, mitigate the detrimental impact on their innovative activities. Shapiro (2000) and Bessen (2003) suggested similar ideas. They argued that patent-oriented strategic instruments, such as patent pooling or cross-licensing, can resolve the problems associated with patent thickets. Likewise, Cockburn et al. (2010) showed that the impact of the patent thicket on a firm's innovative activity is dependent on the firm's patent licensing activity, which implies that patent holdup risk can be managed strategically.

2.3 Model

What is the nature of the strategic benefits that a firm can gain over its market competitor when it exploits the patent holdup risk of the rival firm? How, if at all, does such a benefit incentivize the focal firm's external patents acquisition?

Suppose that there are three firms. Firm 1 and firm 2 are symmetric and in downstream market competition. They produce imperfectly substitutable products. The product substitutability is parameterized into $\theta \in [0, 1]$. Firm 1 faces the inverse demand curve $p_1 = a - b(q_1 + \theta q_2)$ while firm 2 faces $p_2 = a - b(q_2 + \theta q_1)$ where a and b are positive numbers (Bowley, 1924). When θ is 0, each firm faces its market demand whereas they engage in duopolistic market competition with a perfectly substitutable product if $\theta = 1$. For simplicity, I assume that firm 1 and firm 2 both have the constant marginal production cost, c. Firm 3 owns a patent for an essential technological input for the two other firms' production. It is assumed that cost for inventing around this patent is substantial while firm 3 competes with neither of them in the downstream market. The product substitutability, the inverse demand curves, and the marginal production cost are common information.

2.3.1 When firm 3 keeps the patents

Given the technological importance of the patent for the production of firms 1 and 2, these two firms receive licenses to the patents owned by firm 3. In return, firm 3 earns a certain fraction (i.e., royalty rate r) of firm 1 and firm 2's market revenues as the licensing fee. Given r, firm 1 and firm 2 maximize their profits as follows;

$$\max_{q_i} q_i\{(1-r)(a-bq_i-b\theta q_j)-c\}, i,j \in \{1,2\}, i \neq j \tag{2.1}$$

In quantity competition, firm 1 and 2 produce $\tilde{q}_i = \frac{a(1-r)-c}{b(2+\theta)(1-r)}$. Given the two firms' best responses, firm 3 decides r to maximize its profit as follow:

$$\max_{r} \pi_3 := \pi_0 + r\tilde{q}_1(a-b\tilde{q}_1-b\theta\tilde{q}_2) + r\tilde{q}_2(a-b\tilde{q}_2-b\theta\tilde{q}_1) \tag{2.2}$$

where π_0 is the market profit of firm 3, which is independent from firm 1 and firm 2's market operation. Firm 3 charges r such that $\frac{\partial \pi_3}{\partial r} = 0$.

2.3.2 When the patent is transferred to firm 1(or 2)

Consider that firm 3 sells patents to either firm 1 or firm 2. For simplicity, suppose that firm 1 becomes the new owner of the patent. With r now given by firm 1, firm 1 and firm 2 decide their optimal production level, by solving the following profit maximization problems;

$$
\begin{aligned}
Firm1 : \max_{q_1} q_1(a - bq_1 - b\theta q_2 - c) + rq_2(a - bq_2 - b\theta q_1) \\
Firm2 : \max_{q_2} q_2\{(1 - r)(a - bq_2 - b\theta q_1) - c\}
\end{aligned}
\tag{2.3}
$$

Firm 1 and firm 2's conditional best responses are $\tilde{q_1} = \frac{a-c-bq_2\theta(1+r)}{2b}$, $\tilde{q_2} = \frac{(1-r)(a-b\theta q_1)-c}{2b(1-r)}$. Firm 1 decides r to maximize its profit, given $\tilde{q_1}$ and $\tilde{q_2}$.

This model accommodates the concepts of revenue effect and rent dissipation effect of patent licensing (Arora and Fosfuri, 2003; Arora et al., 2004, 2013; Motohashi, 2008; Arora and Gambardella, 2010; Kani and Motohashi, 2012). Revenue effect refers to the royalty revenue that the patent owner can obtain by licensing owning patent to other firms. Rent dissipation effect refers to the patent holder's profit loss due to the licensee's market operation with the licensed patent by the patent holder. The rent dissipation effect increases in the intensity of downstream market competition between the patent holder and the licensee.

In the firm 1's profit function, $-b\theta q_2$ captures the rent dissipation effect because it corresponds to the loss of market revenue of firm 1 by the rival's market operation with the licensed patent. $rq_2(a - bq_2 - b\theta q_1)$ captures the revenue effect because it is the rent revenue that firm 1 obtains from firm 2 as a result of licensing.

2.3.3 Comparative Analysis

For non-linearity of the system equations, I find numerical solutions, setting $a = 5, b = 1$, and $c = 1$ with variation in θ from 0 to 1.

Royalty rate. The first panel (Northwest) of Figure 2.1 profiles the optimal level of r that the patent holder will charge to licensees before (black solid) and after (blue solid) the patent transfer. First, in both cases, r increases in θ. This indicates that the greater intensity of market competition between firm 1 and firm 2, the larger that the royalty fee charged by the patent holder will be. Second, if firm 1 becomes the new patent owner, when θ

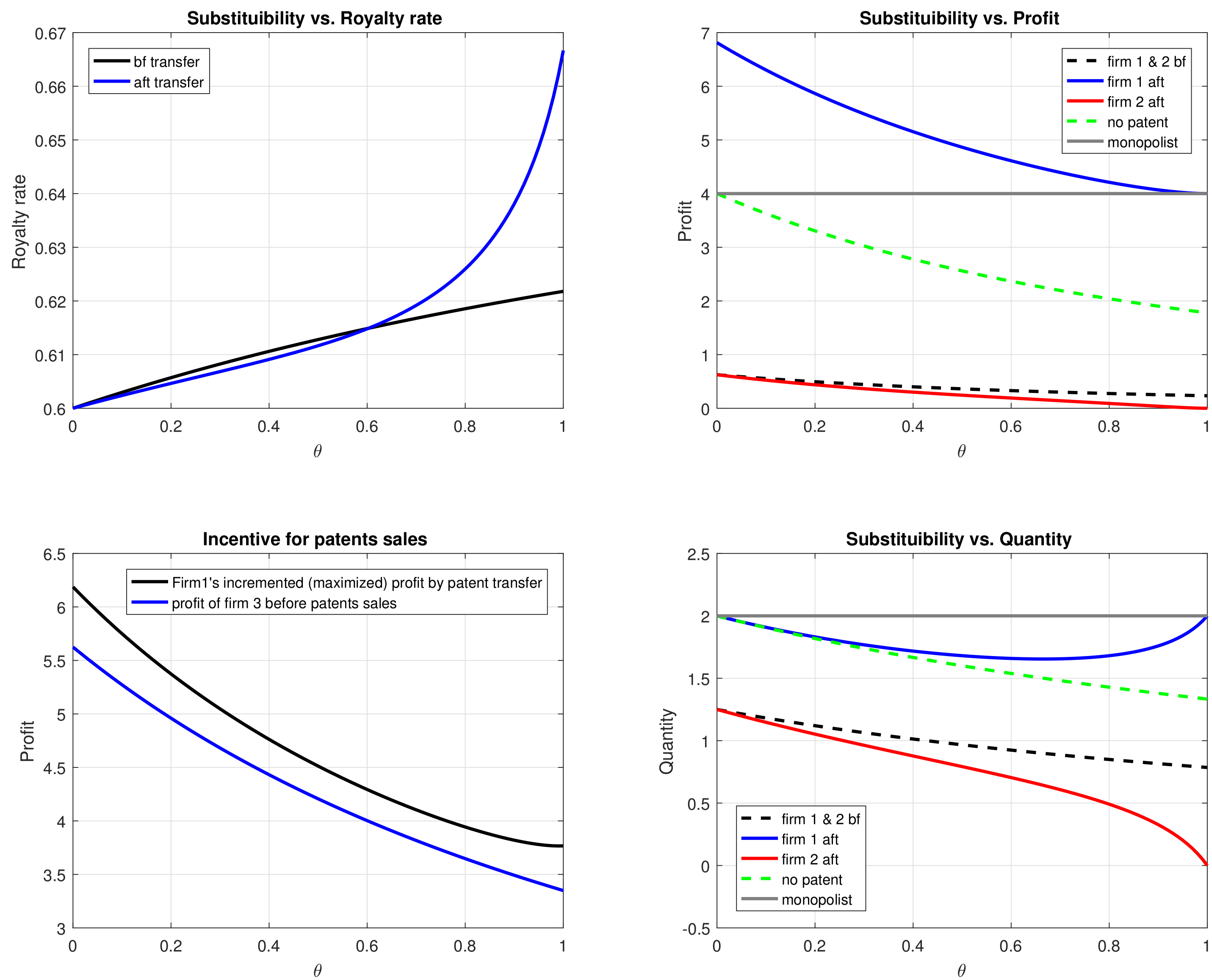


Figure 2.1: Predictions by the model

is sufficiently large, the royalty rate that firm 1 will charge firm 2 becomes substantially greater than what was charged by firm 3. This indicates that if firm 1 and firm 2 are close enough in the downstream market space, firm 1's patent purchase and the probable re-negotiation for licensing will impose a greater royalty cost per revenue on firm 2.

Profit. The second panel (Northeast) of Figure 2.1 plots firm 1 and firm 2's maximized level of profits by θ when firm 2 continues to receive the license at the given royalty rate r. After firm 1 purchases the patent, it earns more profit (blue solid) than firm 2 (red solid) when $0 < \theta < 1$. If the patent on the technology does not exist (green dashed), firm 1's profit when it purchases the patent from firm 3 is greater than that when the two firms are in typical duopolistic market competition. Firm 1's profit if it owns the patent also exceeds its monopolistic market profit (gray solid). These findings indicate that firm 1 has an economic incentive to purchase the patent as long as firm 1 can compel firm 2 to pay to license the patent at the desired royalty rate.

The improvement of firm 1's profit originates from the fact that firm 1 becomes capable of internalizing the externality of its rival's market operation through enforcement of the patent license. In doing so, firm 1 can manipulate firm 2's production level while gaining rent revenue. In contrast, firm 3 has no stakes in increasing the royalty rate as high as firm 1 will, because imposing excessive rent reduces the market revenue of the licensees and it curtails the royalty revenue for firm 3 accordingly while doing so gives no benefits in downstream market competition.

Firm 3's incentive for patent sale. Does firm 3 have an economic incentive to sell the patent to firm 1 (or firm 2) in the first place? I examine whether firm 3 can enhance its profit by selling the patent to firm 1, compared to the profit that firm 3 earns when it keeps the patent. Firm 1's maximum willingness to pay (WTP) to purchase firm 3's patent is firm 1's expected incremental profit from this patent acquisition. The third panel on the southwest of Figure 2.1 profiles firm 1's maximum WTP for the patent-purchase and firm 3' profit before the patent-transfer. Firm 1's calculated incremental profit from the patent acquisition (Black solid line) exceeds firm 3's when firm 3 keeps the patent (Blue solid line), which indicates that the patent ownership transfer from firm 3 to firm 1 enhances both firms' profits.[1]

Patents selection for purchase. The comparative statistics reveal that there is an economic incentive for a firm to purchase patent if this firm can compel rival firms to pay to license these patents at the desired royalty rate. Thus, the focal firm has an incentive for purchasing patents that are critical to its rivals' market operation.

2.3.4 Impact of patent ownership transfer on rival's innovative activity

How does a firm's patent purchase affect the rival's innovative activity if the patent is critical to the rival's market operation and, thus the patent purchase imposes a greater risk of patent holdup on the rival?

Consider that firm 1 and 2 make products by combining two technological elements, E1 and E2. E1 is the group of technologies that are replaceable for or have technological dependency on the patent that is purchased by firm 1. The patent of interest cover h-technologies for E1. E2 is for technologies that are not relevant to the patents. The number of technologies that the firm obtains for E1 and E2 for production is x and y, respectively.

I model a firm's production function into a Cobb-Douglas function of x and y, (i.e., $q(x, y) = A_0 x^{\alpha} y^{\beta}$). I assume that other inputs for production such as labor or capital are independent of the patents transfer. The firm pays P_x and P_y for developing one additional unit of technology of E1 and E2 in the initial setting (i.e., firm 3 owns the patent), respectively. For comparative statistics, I set $P_y = 1$.

Before the patent transfer. Firm 1 and firm 2 were presumed to receive licenses on the patent from firm 3 before the patent transfer. Firm 1 and firm 2's optimal production levels

[1] The fact that the calculated maximum WTP of firm 1 decreases as θ increases, should not be interpreted as the greater the market competition intensity between firms 1 and 2, the lower firm 1's incentive to purchase the patents. This is because the small value of θ means that firm 1 and firm 2 are in a different market. If firm 1 compels firm 2 that is in a different market to receive the license on firm 1's patent, firm 1 effectively earns the market profit from own market operation and firm 2's market operation, which double the profit size.

are determined by the result of market competition between them with the given royalty rate r_0^* by firm 3. For firm 2, this rate of royalty determines the desired level of x and y by solving the following cost minimization problem:

$$\min_{x,y} q_{20}^* r_0^*(a - bq_{20}^* - b\theta q_{10}^*) + P_x x + y, s.t. q_{20}^* = A_0(x+h)^\alpha y^\beta \tag{2.4}$$

where q_{10}^* and q_{20}^* are firm 1 and firm 2's optimal production level before the patent ownership transfer. The solutions are $x_0^* = \{\frac{q_{20}^*}{A_0}(\frac{\alpha}{\beta P_x})^\beta\}^{\frac{1}{\alpha+\beta}} - h$ and $y_0^* = \{\frac{q_{20}^*}{A_0}(\frac{\beta P_x}{\alpha})^\alpha\}^{\frac{1}{\alpha+\beta}}$. Firm 2's relative R&D outcome for E1 over E2 is $\lambda_0^* : \frac{x_0^*}{y_0^*} = \frac{\alpha}{\beta P_x} - h\{\frac{A_0}{q_{20}^*}(\frac{\alpha}{\beta P_x})^\alpha\}^{\frac{1}{\alpha+\beta}}$.

After the patent-transfer. After the patent is transferred to firm 1, firm 2 expects that its optimal production level will decrease if it continues to pay to license to the patent (see Figure 2.1).

Assuming that the firm 1 takes the take-it-or-leave-it (TIOLI) strategy, if the patented technology is replaceable by other patented technologies of E1, firm 2 considers two options: keep paying to license the patent from firm 1 at the increased rate of royalty or inventing around the patent.

When firm 2 chooses to pay for the license, firm 2 continues to use h-technologies for E1. In return, the firm pays royalties at the given rate r_L^* to firm 1 while the production level changes to q_{2L}^*. Then, firm 2 decides x and y by solving the cost minimization problem as it did when it was paying to license h-technologies from firm 3. The solutions are $x_L^* = \{\frac{q_{2L}^*}{A_0}(\frac{\alpha}{\beta P_x})^\beta\}^{\frac{1}{\alpha+\beta}} - h$ and $y_L^* = \{\frac{q_{2L}^*}{A_0}(\frac{\beta P_x}{\alpha})^\alpha\}^{\frac{1}{\alpha+\beta}}$. Firm 2's relative R&D outcome for E1 over E2 is calculated as $\lambda_L^* : \frac{x_L^*}{y_L^*} = \frac{\alpha}{\beta P_x} - h\{\frac{A_0}{q_{2L}^*}(\frac{\alpha}{\beta P_x})^\alpha\}^{\frac{1}{\alpha+\beta}}$. Because $q_{2L}^* < q_{20}^*$ (see the southeast panel of Figure 2.1), $x_L^* < x_0^*$, $y_L^* < y_0^*$, and $\lambda_L^* < \lambda_0^*$.

If firm 2 chooses to invent-around, the firm develops all the necessary technologies for E1 and E2 through internal R&D. Doing so frees firm 2 from a license contract with firm 1, but making firm 2 face the greater internal R&D cost for E1 (P_z) due to the probable cost for inventing around h-technologies. Firm 2 solves the following cost minimization problem:

$$\min_{x,y} P_z x + y, s.t. q^*_{2D} = A_0 x^\alpha y^\beta \tag{2.5}$$

The solutions are $x^*_D = \{\frac{q^*_{2D}}{A_0}(\frac{\alpha}{\beta P_z})^\beta\}^{\frac{1}{\alpha+\beta}}$ and $y^*_D = \{\frac{q^*_{2D}}{A_0}(\frac{\beta P_z}{\alpha})^\alpha\}^{\frac{1}{\alpha+\beta}}$. Firm 2's relative R&D outcome for E1 over E2 is calculated as $\lambda^*_D : \frac{x^*_D}{y^*_D} = \frac{\alpha}{\beta P_z}$. $\lambda^*_D < \lambda^*_0$ if $P_z > \tilde{P}_x$ where $\tilde{P}_x = P_x[1 - h\{(\frac{A_0}{q^*_{20}})(\frac{\beta P_x}{\alpha})^\beta\}^{\frac{1}{\alpha+\beta}}]^{-1} > P_x$ while $\lambda^*_D \geq \lambda^*_0$, otherwise. This indicates that if the increased R&D cost of inventing around the patent is large enough (i.e., exceeds the cutoff $\tilde{P}_x$), firm 2's relative R&D outcome for E1 over E2 decreases as a result of the patents transfer to firm 1. It can be expected that λ^*_D increases due to the patents transfer if the cost of inventing around the patent is not that large. This case does not fall into the situation where patent holdup is likely to occur.

This consequence is caused by the fact that firm 1's patents purchase increases the marginal production cost of firm 2. When firm 2 continues to license the patents from firm 1, it faces increased royalty rates while having a greater R&D cost if firm 2 invents around firm 1's patent. Therefore, as long as firm 1 can compel firm 2 to continue paying to license the patents because the cost for replacing the patented technology is excessively high, firm 1's patent purchase negatively impacts firm 2's relative R&D outcome for E1 over E2.

What if the patent of interest is essential and not replaceable by other technologies of E1? The patent holdup theory asserts that if a patent that covers essential input for production is owned by other entity who may exploit the patent holdup risk of the rival firm, this rival firm becomes reluctant to acquire the technologies that depend on the patent at holdup risk.

As shown in section 3.3, firm 1 has the incentive to purchase patents if it can compel firm 2 to pay for the license on the patent at an increased royalty rate by leveraging firm 2's patent holdup risk. Doing so allows firm 1 to maneuver firm 2's market operation, which enhances firm 1's market profit in return. Then, firm 2 will be reluctant to engage in the R&D activity for obtaining technologies dependent on firm 1-purchased patent, expecting holdup. Accordingly, firm 2's relative R&D outcome for E1 over E2 decreases.

The constructed model above draws the same conclusion. If the patent covers essential technology for firm 2's production, the cost of inventing around the patent will likely be excessively high (i.e., $P_z >> \tilde{P}_x$). Hence, firm 2's relative R&D outcome for E1 over E2 decreases.

To summarize, firm 1's patent purchase can impose a greater level of ex-post patent holdup risk to firm 2, making firm 2 relative less active in developing the relevant technologies to the firm1-purchased patent. More formally: **If a firm purchases a patent that covers crucial technical input for rival firm's market operation, the rival becomes relatively less active in developing the relevant technologies to the patent the focal firm purchased.**

2.4 Empirical Analysis

2.4.1 Nortel's Patent Auction in 2011

The empirical work of this study was based on the case of Nortel's patent auction. Nortel, which was a Canadian telecommunications equipment company, tried to liquidate their patents (largely on telecommunications technology) as part of bankruptcy, and they opened a patents auction on June 27, 2011.

Five parties participated: Apple, the Ericsson Consortium (a consortium of Ericsson, Research in Motion [RIM], Microsoft [MS], Sony, and EMC), Google, Intel, and Norpax Inc. Intel made an initial bid of over $900 million, after which Nortel raised the threshold for bidding increments to $100 million. As a result, Norpax Inc. decided to stop further bidding. The Ericsson Consortium gave up further bidding after three more rounds. Interestingly, Apple and the Ericsson Consortium made a partnership and continued bidding together under the name of Rockstar Bidco (hereafter "Rockstar"). As a result, Rockstar came to have greater bidding power than Google and Intel, and after the sixth round of bidding, Intel decided to exit the auction. Just as Apple and the Ericsson Consortium had done, Google partnered with Intel, and they bid together as a consortium named Rangers.

At that point, the auction turned into a competition between two large consortia for the acquisition of the Nortel patents: Rockstar (Apple + MS + RIM + Sony + Ericsson + EMC) versus Rangers (Google + Intel). Finally, Rockstar won the auction on June 30, 2011, with a bid to pay $4.5 billion for the Nortel patents.[2]

In 2012, about half of the Nortel patents were redistributed to the three member-companies of Rockstar (Apple, MS, and RIM). The remaining patents were transferred to either a patent assertion entity (i.e., Spherix Inc.) or a defensive patent aggregator (i.e., RPX Corp). None of the patents were re-transferred to Google or Intel.

This case is useful for testing the present study's hypothesis for the following reasons. First, the stakes for the participating firms in acquiring the Nortel patents before their competitors could were high (Nicholson, 2011).[3] Nortel owned many high-quality patents in communications technology, including SEPs that are crucial for making smart devices. Most of the auction participants owned patent portfolios that were weak in communications technology and were exposed to increasing patent infringement disputes during the so-called "era of smartphone patent war" (Lloyd et al., 2011) on communications technology patents (Raghu et al., 2008; Chia, 2012; Teece et al., 2014). For this reason, they were desperate to strengthen their patent portfolios, especially with regard to communications technology patents. Nortel's patent auction was a unique opportunity to acquire a large number of high-quality communications technology patents all at once.

Second, the auction bidders were mutual rivals in the smart device market, whereas Nortel was not. Hence, from the perspective of Rangers, Rockstar's winning bid for the Nortel patents was a patent purchase by a rival; this scenario fits in the setting of the constructed model.

Third, the auction result was essentially an external shock to the bidders because the result of the auction was so difficult to predict. The fact that some firms that had ceased

2 The last bidding price that Rangers made was $4 billion. See https://www.theguardian.com/technology/2011/jul/02/google-pi-auction-bid

3 https://www.theguardian.com/technology/2011/jul/01/nortel-patents-sold-apple-sonymicrosoft.

bidding at an early stage were able to continue bidding later through unexpected partnerships with other leading bidders indicates how the auction result was close to an exogenous event for the auction bidders.

By utilizing these features, I identify the impact of the transfer of the Nortel patents on the innovative activities of the losing firms. In this respect, I consider the winning group, Rockstar, to be the comparison group to the losing group, Rangers, because the auction winners avoided being subject to the Nortel patents' ex-post patent holdup risk after the auction.

According to the derived hypothesis, the bid-losing firms would face increased patent holdup risk due to the auction result, which would make them less active in developing technologies that are related to the Nortel patents. Because patents filed by a firm can be used as a proxy for the outcome of the firm's innovative activities (i.e., Pakes and Griliches, 1984; Griliches, 1990), I tested the hypothesis by examining the post-auction differences in outcomes of Nortel patent relevant technologies between the auction winners—the Rockstar firms—and the losing Rangers firms using the difference-in-difference (DiD) approach.

2.4.2 Data

Nortel patents transferred to Rockstar

I began by identifying the US patents that were transferred from Nortel to Rockstar using the patent assignment database provided by the US Patent and Trademark Office (USPTO) (Graham et al., 2018). My initial search found 4,129 patents. While it is known that about 6,000 patents were transferred from Nortel to Rockstar through the auction, the discrepancy in these numbers is caused by the fact that the database does not contain information about pending patent applications and patents granted by non-US authorities.

I included grant patents in the sample and excluded patents that were filed after June 30, 2011. These procedures helped identify the patents that were actually subject to the auction, which resulted in a sample containing 3,574 patents. Out of the total sample, there were 971, 218, and 210 patents that were redistributed to Apple, MS, and RIM, respectively, in 2012. Among the remaining patents, 2,129 were resold to RPX, while Rockstar (including its subsidiary) retained 41 patents, and Spherix Inc., which was known to be a patent assertion entity, acquired ownership of five patents (see Figure 2.2).

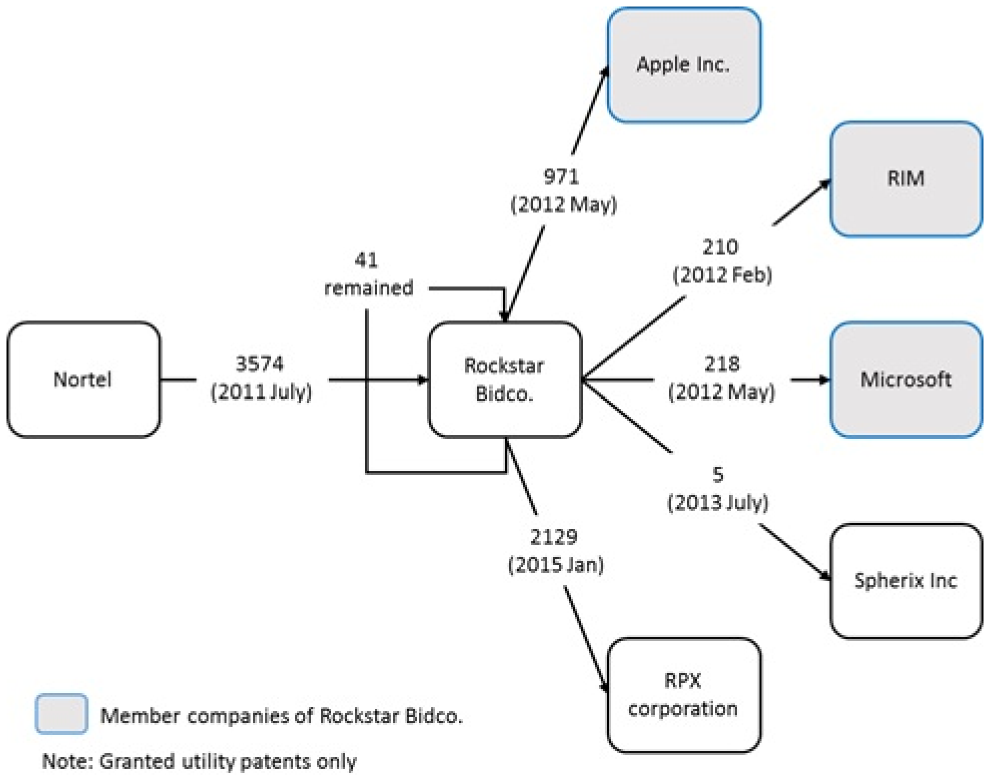


Figure 2.2: Redistribution of the Nortel patents after the auction

Patents filed by the auction bidders

Next, I collected information about US grant patents that had been filed by the auction participants for a time period starting four years before the auction and ending four years after its end date (i.e., July 1, 2007, through June 30, 2015). I then divided these patents into two groups. The first group, labeled WIN, comprised the patents that were filed by the firms that won the auction and were now the new owners of the Nortel patents: Apple, MS, and RIM. The other group, labeled LOSE, contained the patents that were filed by the two losing firms, Google and Intel, who continued bidding until the final round but failed to acquire the Nortel patents.

To identify the patents that were filed by these firms, I searched for patents where the owners' names had been changed from a person's name to one of the firms' names through an employer—inventor type (EIT) transaction. Because patent ownership change through an EIT is based upon contractual obligations a corporate inventor has to the hiring firm (Graham et al., 2018), patents transferred in this way can be considered to have been originally filed by the focal firm.[4] Detailed information about the 42,871 US patents was obtained from patenteview.org, which is serviced by the USPTO.

2.4.3 Variables and the Empirical Model

I employed two dependent variables that operationalize the technological relatedness between the Nortel patents and patents filed by the auction bidders. The first dependent variable was a binary variable labeled **Comm Tech** that took the value of 1 for patents in the National Bureau of Economic Research (NBER) subcategory of communications technology; otherwise, it took the value of 0. Most of the Nortel patents were related to communications technology. Communications technology is often developed cumulatively, which implies that a particular technology in this field has greater relatedness or dependency on other communications technologies than noncommunications technologies would. Hence, the present study's hypothesis can be tested by comparing the post-auction odds of the auction winners and losers filing communications technology patents rather

[4] Under US patent law, initial patent ownership is conferred to inventors for patents that were filed before September 16th, 2012 (pre-America Invents Act [AIA]). For patents filed in the post-AIA period, the applicant (either the inventor or the employer of the inventor) can be the initial owner. Hence, patents that were once transferred to firms via employerinventor type transactions can be considered as "patents" originally filed by the firms if the patents were filed before the AIA. However, for patents filed after the AIA, it is difficult to identify the initial patent owner in the given database. This is due to the fact that the patent assignment database provides information about patent ownership transfer, whereas the official patent search database provided by the USPTO gives information about the "current" patent owner. Due to this difficulty, I only retrieved patents that were transferred to the firm of interest through employerinventor transaction types for all patents filed after the AIA as well. Although this sampling strategy may capture only part of the population of patents filed by the firms of interest, cross-validation with a patent list obtained from a different data source, the Derwent Innovation Index, showed that there was no substantial discrepancy in the number of retrieved patents.

than non-communications technology patents.

A patent citation is made when previously patented inventions limit the legal scope of the new invention in question (Trajtenberg et al., 1997; Hall and Ziedonis, 2001). A patent citation also indicates that the pair of cited and citing patents are technologically interrelated (see Jaffe and de Rassenfosse, 2017). Studies have used patent citations as a proxy for a technological link between the cited and citing patents, considering it a paper trail of knowledge flow (e.g., Jaffe et al., 1993). Following this line of research, I defined two patents as having technological overlap, hereafter **Tech Overlap**, if the two patents are connected through a patent citation in one of the following ways: (1) when one patent cites the other (**Direct Citation**), or (2) when the two patents cite the same third patent(s) (**Shared Reference**).

For patents that were filed by firms in the WIN group, **Tech Overlap** took the value of 1 if the patent cites, or is cited by, or if they share at least one backward citation with a Nortel patent. For patents filed by firms in the LOSE group, **Tech Overlap** took the value of 1 if the patent is in a citation relationship with any Nortel patent purchased by WIN group firms.

Three sets of independent variables were created to employ the DiD approach. First, I created a set of time dummy variables (T) that regrouped the patents into nine blocks, each with a duration of one year, based on the patent application date. Because the auction ended on June 30, 2011, patents filed from July 1, 2010, through June 30, 2011, became the reference group (T+0).

Second, I introduced a binary variable that took the value of 1 if the patent of interest was filed by a firm in the LOSE group (LOSE): this takes into consideration the difference in the dependent variable at T + 0 between the WIN and LOSE groups.

Third, I generated interaction terms between the time dummy variables and LOSE. The hypothesis anticipates statistically significant negative coefficients for $LOSE \times T + n, n > 0$.

I fit the data to the logit model because the nature of the variable of interest is odds (i.e., λ, see the section 3.4). In the regression analysis, I used cluster robust standard errors by firms to take into account within-group correlation between patents filed by the same firm because those patents may have a systematic correlation with each other while differing from patents filed by other firms. The following formula describes the specification of the econometric model.

$$log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 \times LOSE_i + \sum_{j=-4, j\neq 0}^{4} \gamma_j \times T_{ji} + \sum_{k=-4, k\neq 0}^{4} \alpha_k \times T_{ki} \times LOSE_i + \epsilon_i \quad (2.6)$$

where p_i is the latent variable of the dependent variable for patent i, $LOSE_i$ takes the value of 1 if patent i was filed by a firm in the LOSE-group, T_{ji} takes the value of 1 if patent i was filed in a jth period counted from the reference period, T is the time dummy variables, and ϵ_i is the error term.

2.5 Results

2.5.1 Descriptive Analysis

The summary statistics in Table 2.1 show that about 86% of the Nortel patents redistributed to the three member-companies of Rockstar are communications technology patents.

Table 2.2 shows the number of patents filed by each firm during the period of observation. The decrease in the number of patents filed beginning in the fourth year after the auction is due to the delay in publishing and indexing patent applications in the patent assignment database.

Figure 2.3 presents the average share of communications technology patents. The solid and dashed lines represent the share of communications technology patents filed by, respectively, firms in the WIN group and firms in the LOSE group.

The graphical comparison in Figure 2.3 reveals that firms in the WIN group (solid black line) and firms in the LOSE group (dashed black line) had similar pre-auction time

Table 2.1: Technology class profile of the Nortel patents

Tech Field (NBER-Subcategory)	Total	Redistributed patents	Leftover patents	Share of redistributed patents
Communications	2546	1190	1356	46.7%
Computer Hardware & Software	537	118	419	22.0%
Optics	131	2	129	1.5%
Electrical Devices	76	50	26	65.8%
Electronic business methods and software	71	10	61	14.1%
Information Storage	55	2	53	3.6%
Miscellaneous	35	8	27	22.9%
Power Systems	32	11	21	34.4%
Semiconductor Devices	25	1	24	4.0%
Computer Peripherals	20	4	16	20.0%
Measuring & Testing	15	1	14	6.7%
Electrical Lighting	11	0	11	0.0%
Metal Working	8	1	7	12.5%
Nuclear & X-rays	7	1	6	14.3%
Heating	2	0	2	0.0%
Apparel & Textile	1	0	1	0.0%
Amusement Devices	1	0	1	0.0%
Transportation	1	0	1	0.0%
Total	3574	1399	2175	39.1%

Table 2.2: Technology class profile of the Nortel patents

Year from the auction	APP	MS	RIM	GOOG	INTL	TOTAL
-4	500	2,045	443	271	1,129	4,388
-3	456	2,008	375	335	966	4,140
-2	710	1,732	451	370	624	3,887
-1	731	1,457	771	456	685	4,100
0	904	1,736	831	962	613	5,046
1	901	1,521	1,014	2,489	589	6,514
2	1,319	1,239	979	2,499	2,196	8,232
3	590	678	330	1,603	1,227	4,428
4	348	332	122	782	552	2,136
Total	6,459	12,748	5,316	9,767	8,581	42,871

trends for their likelihood of filing a communications technology patent. After the auction (right of the red dashed line), the likelihood of filing a communications technology patent increased for firms in the WIN group, whereas it decreased substantially for firms in the LOSE group. Interestingly, the likelihood began increasing for firms in the LOSE group in the second year after the auction.

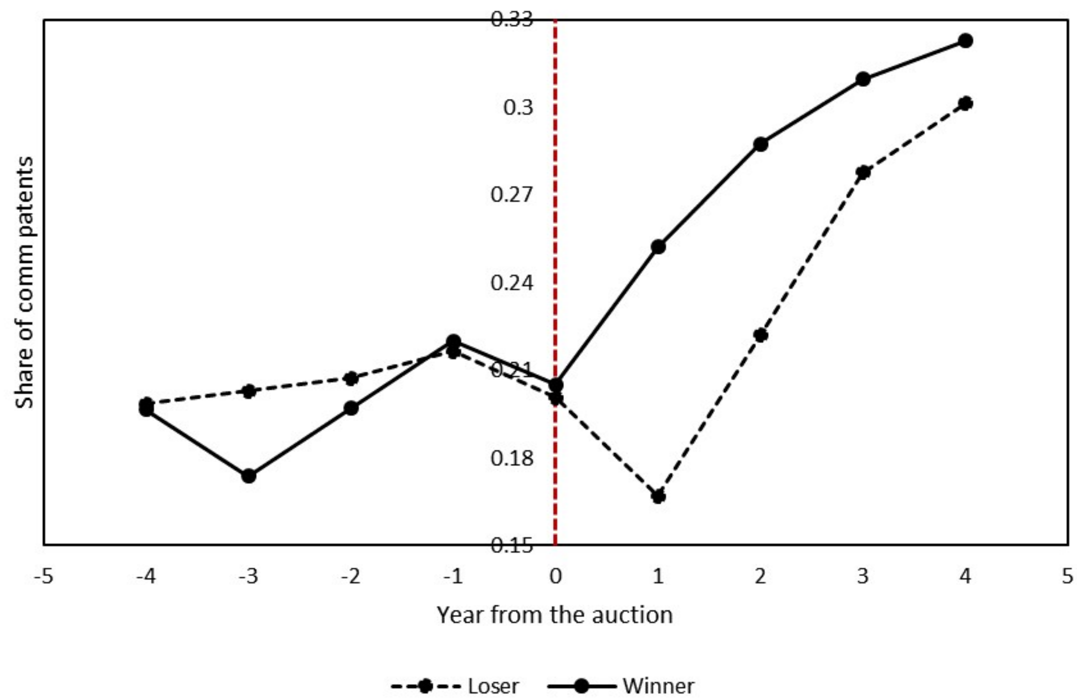


Figure 2.3: Share of communications technology patents

Figure 2.4 depicts the average share of patents that have technological overlap with Nortel patents. The pre-auction patent filing time trend for the two groups is seemingly parallel. However, one year after the auction, the patent filing time trend begins differentiating between firms in the WIN group and firms in the LOSE group.

2.5.2 Regression Analysis

Table 2.3 presents the main regression results. The first column reports the estimated logit coefficients, employing **Comm Tech** as the dependent variable. The coefficients in the second column show the estimated average marginal effect (AME).

First, the coefficients of interaction terms between the pre-auction time dummy variables and LOSE were statistically insignificant at the 0.1 significance level ($LOSE \times T - 4$ to $LOSE \times T - 1$). This observation confirms that firms in the WIN and LOSE groups had statistically parallel time trends for the log odds of filing communications technology patents before the auction, but after the auction, the coefficient of $LOSE \times T + 1$

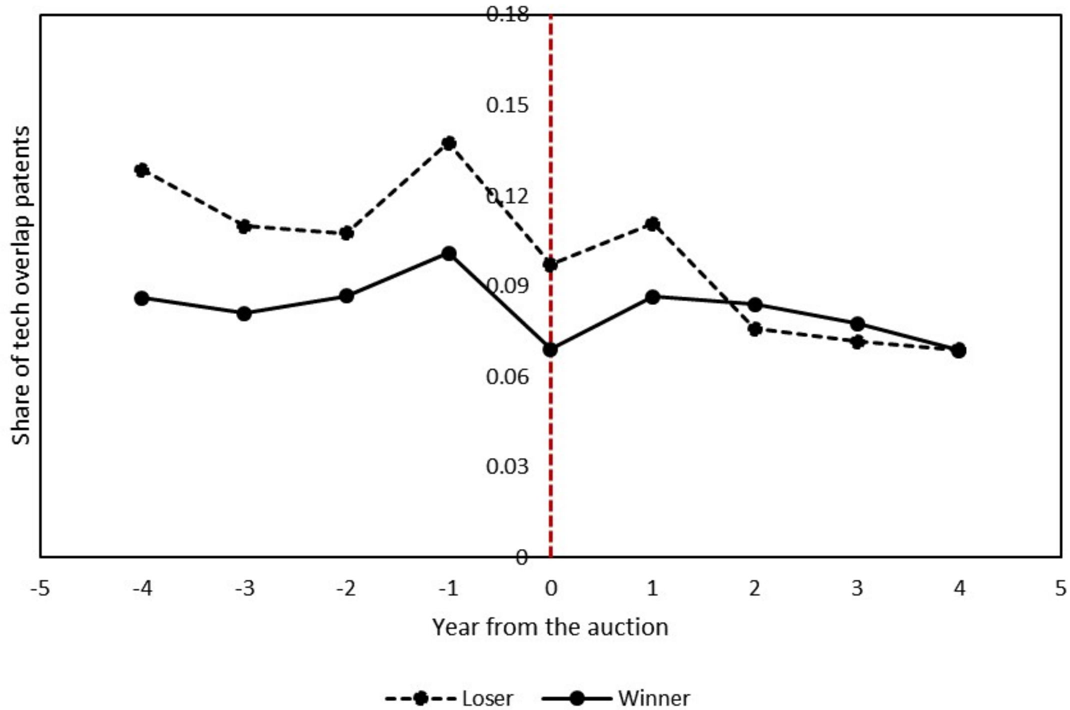


Figure 2.4: Share of Tech Overlap Patents

became negative and statistically significant at the 0.01 significance level (0.493). The AME presented in the second column shows that the LOSE firms' likelihood of filing communications technology patents decreased by 8.5% points compared to firms in the WIN group one year after the auction. Interestingly, this impact disappears starting in the second year after the auction. The post-auction interaction terms beginning in the second year ($LOSE \times T+2$ to $LOSE \times T+4$) become statistically insignificant at the 0.1 significance level.

The third and fourth columns report the estimated logit and AME coefficients, employing **Tech Overlap** as the dependent variable. The interaction terms from $LOSE \times T-4$ to $LOSE \times T-1$ are statistically insignificant at the 0.1 significance level. This result indicates that the LOSE and WIN groups' pre-auction time trends for the odds of filing patents that technologically overlap with Nortel patents were statistically parallel. The coefficients of $LOSE \times T+1$ and $LOSE \times T+3$ are negative and statistically significant at

Table 2.3: Main regression

	DV:Comm Tech		DV: Tech Overlap	
	Logit(Comm Tech)	AME(Comm Tech)	Logit(Tech Over)	AME(Tech Over)
LOSEXT-4	0.0412	0.00713	0.0792	0.00635
	(0.204)	(0.0361)	(0.182)	(0.0142)
LOSEXT-3	0.220	0.0381	-0.0335	-0.00268
	(0.153)	(0.0298)	(0.241)	(0.0195)
LOSEXT-2	0.0911	0.0158	-0.132	-0.0106
	(0.148)	(0.0285)	(0.261)	(0.0213)
LOSEXT-1	0.00709	0.00123	-0.0203	-0.00162
	(0.0486)	(0.00827)	(0.114)	(0.00907)
LOSEXT+1	-0.493***	-0.0855***	-0.0953*	-0.00764*
	(0.0502)	(0.00878)	(0.0490)	(0.00450)
LOSEXT+2	-0.319	-0.0553*	-0.481**	-0.0386*
	(0.215)	(0.0334)	(0.241)	(0.0201)
LOSEXT+3	-0.127	-0.0220	-0.455*	-0.0365*
	(0.240)	(0.0381)	(0.264)	(0.0201)
LOSEXT+4	-0.0728	-0.0126	-0.364	-0.0292
	(0.335)	(0.0563)	(0.435)	(0.0332)
T-4	-0.0541	-0.00937	0.237	0.0190
	(0.165)	(0.0302)	(0.144)	(0.0132)
T-3	-0.205	-0.0356	0.171	0.0137
	(0.140)	(0.0285)	(0.199)	(0.0171)
T-2	-0.0504	-0.00874	0.246**	0.0197*
	(0.139)	(0.0255)	(0.120)	(0.0109)
T-1	0.0889*	0.0154	0.414***	0.0332***
	(0.0455)	(0.0104)	(0.103)	(0.00626)
T+1	0.268***	0.0465***	0.242***	0.0194***
	(0.0482)	(0.00537)	(0.0388)	(0.00472)
T+2	0.447**	0.0775***	0.210	0.0169
	(0.180)	(0.0208)	(0.234)	(0.0191)
T+3	0.553**	0.0959***	0.124	0.00998
	(0.240)	(0.0269)	(0.243)	(0.0191)
T+4	0.614*	0.106***	-0.00882	-0.000707
	(0.330)	(0.0405)	(0.407)	(0.0327)
LOSE	-0.0278	-0.00482	0.371**	0.0297**
	(0.712)	(0.124)	(0.173)	(0.0119)
Constant	-1.355**		-2.600***	
	(0.630)		(0.165)	
Pseudo R^2	0.010		0.006	
Observations	42871	42871	42871	42871

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Cluster robust standard errors in parentheses

the 0.1 significance level, while the coefficient of $LOSE \times T + 2$ is negative and statistically significant at the 0.05 significance level. The estimated AME shows that firms in the

LOSE group became 0.8%, 3.9%, and 3.7% points less likely to develop inventions with technological overlap to Nortel patents than in the reference year as compared to firms in the WIN group.

This observed effect seems to disappear gradually over time after the auction. The size of the coefficients of the post-auction interaction terms between the time dummy variables and LOSE in the second through fourth years after the auction ($LOSE \times T+2$ to $LOSE \times T+4$) decreased, while the coefficients for $LOSE \times T+4$ became statistically insignificant at the 0.1 significance level.

2.5.3 Robustness Check

Estimation without cluster standard error option

Correcting the standard error (SE) using the typical cluster SE estimation procedure may result in over-rejection of the null hypothesis when there are few clusters in the data (Cameron and Miller, 2015). To check the robustness of the findings for this potential problem, I conducted regression analysis without the cluster option.

Table 2.4 reports the results. The first two columns present the estimated logit and AME coefficients when employing **Comm Tech** as the dependent variable. The last two columns report the logit and AME coefficients when employing **Tech Overlap** as the dependent variable. The results are largely consistent with the main regression result.

Alternative indicators of technological overlap between patents

Tech Overlap is a composite variable created from two patent citation-based indicators: **Direct Citation** and **Shared Reference**. To check the robustness of the findings, I ran two separate regressions, one with each of the two binary variables, and the results are shown in Table 2.5.

The first two columns report the regression results employing **Direct Citation** as the dependent variable. In the first column, the estimated logit coefficients of the interaction

Table 2.4: Estimation without cluster standard error option

	DV:Comm Tech		DV: Tech Overlap	
	Logit(Comm tech)	AME(Comm tech)	Logit(Tech over)	AME(Tech over)
LOSEXT-4	0.0412	0.00713	0.0792	0.00635
	(0.111)	(0.0192)	(0.149)	(0.0120)
LOSEXT-3	0.220*	0.0381*	-0.0335	-0.00268
	(0.114)	(0.0197)	(0.156)	(0.0125)
LOSEXT-2	0.0911	0.0158	-0.132	-0.0106
	(0.118)	(0.0205)	(0.163)	(0.0131)
LOSEXT-1	0.00709	0.00123	-0.0203	-0.00162
	(0.113)	(0.0197)	(0.151)	(0.0121)
LOSEXT+1	-0.493***	-0.0855***	-0.0953	-0.00764
	(0.0980)	(0.0170)	(0.137)	(0.0110)
LOSEXT+2	-0.319***	-0.0553***	-0.481***	-0.0386***
	(0.0913)	(0.0158)	(0.136)	(0.0109)
LOSEXT+3	-0.127	-0.0220	-0.455***	-0.0365***
	(0.102)	(0.0177)	(0.161)	(0.0129)
LOSEXT+4	-0.0728	-0.0126	-0.364*	-0.0292*
	(0.122)	(0.0212)	(0.207)	(0.0166)
T-4	-0.0541	-0.00937	0.237**	0.0190**
	(0.0623)	(0.0108)	(0.0935)	(0.00749)
T-3	-0.205***	-0.0356***	0.171*	0.0137*
	(0.0650)	(0.0113)	(0.0960)	(0.00769)
T-2	-0.0504	-0.00874	0.246***	0.0197***
	(0.0629)	(0.0109)	(0.0940)	(0.00754)
T-1	0.0889	0.0154	0.414***	0.0332***
	(0.0611)	(0.0106)	(0.0905)	(0.00726)
T+1	0.268***	0.0465***	0.242***	0.0194***
	(0.0575)	(0.00997)	(0.0903)	(0.00724)
T+2	0.447***	0.0775***	0.210**	0.0169**
	(0.0561)	(0.00970)	(0.0903)	(0.00724)
T+3	0.553***	0.0959***	0.124	0.00998
	(0.0685)	(0.0119)	(0.115)	(0.00922)
T+4	0.614***	0.106***	-0.00882	-0.000707
	(0.0864)	(0.0150)	(0.155)	(0.0124)
LOSE	-0.0278	-0.00482	0.371***	0.0297***
	(0.0757)	(0.0131)	(0.108)	(0.00868)
Constant	-1.355***		-2.600***	
	(0.0420)		(0.0669)	
Pseudo R^2	0.010		0.006	
Observations	42871	42871	42871	42871

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robust standard errors in parentheses

terms between the post-auction time dummy variables and LOSE ($LOSE \times T+2$ and $LOSE \times T+3$) are negative and statistically significant at the 0.01 significance level. The

Table 2.5: Estimation with two alternative measurements of Tech Overlap

	Logit(Direct Cite)	AME(Direct Cite)	Logit(Same Ref)	AME(Same Ref)
LOSEXT-4	0.781***	0.00772**	0.0759	0.00589
	(0.192)	(0.00310)	(0.200)	(0.0152)
LOSEXT-3	-0.413	-0.00409	-0.0153	-0.00118
	(0.255)	(0.00314)	(0.261)	(0.0204)
LOSEXT-2	-0.282	-0.00279	-0.144	-0.0111
	(0.357)	(0.00380)	(0.242)	(0.0192)
LOSEXT-1	-0.196	-0.00194	0.0359	0.00278
	(0.617)	(0.00568)	(0.0710)	(0.00560)
LOSEXT+1	-0.417	-0.00413	-0.117**	-0.00908*
	(0.257)	(0.00292)	(0.0537)	(0.00490)
LOSEXT+2	-0.698***	-0.00691***	-0.499**	-0.0387**
	(0.235)	(0.00172)	(0.234)	(0.0192)
LOSEXT+3	-0.798***	-0.00790***	-0.492*	-0.0382**
	(0.232)	(0.000920)	(0.253)	(0.0187)
LOSEXT+4	-0.0879	-0.000869	-0.478	-0.0371
	(0.712)	(0.00685)	(0.428)	(0.0310)
T-4	-0.188	-0.00186	0.247	0.0192
	(0.168)	(0.00190)	(0.164)	(0.0144)
T-3	1.080***	0.0107***	0.144	0.0112
	(0.165)	(0.00401)	(0.228)	(0.0187)
T-2	0.640*	0.00633	0.233**	0.0181*
	(0.354)	(0.00423)	(0.115)	(0.01000)
T-1	0.705	0.00697	0.358***	0.0278***
	(0.615)	(0.00454)	(0.0585)	(0.00390)
T+1	0.581***	0.00575**	0.241***	0.0187***
	(0.111)	(0.00224)	(0.0482)	(0.00530)
T+2	0.916***	0.00906***	0.198	0.0154
	(0.173)	(0.000358)	(0.228)	(0.0181)
T+3	0.682***	0.00674***	0.125	0.00973
	(0.214)	(0.000748)	(0.234)	(0.0178)
T+4	0.730	0.00722	0.0276	0.00214
	(0.712)	(0.00545)	(0.399)	(0.0308)
LOSE	0.0486	0.000480	0.400**	0.0310***
	(0.461)	(0.00446)	(0.163)	(0.0105)
Constant	-5.102***		-2.636***	
	(0.461)		(0.156)	
Pseudo R^2	0.011		0.006	
Observations	42871	42871	42871	42871

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Cluster robust standard errors in parentheses

estimated AME reported in the second column indicates that LOSE group firms became 0.8% points less likely to file patents with a direct citation relationship to Nortel patents after the second and third years following the auction, as compared to the WIN group.

However, this impact disappeared beginning in the fourth year after the auction.

The last two columns report the regression results employing **Shared Reference** as the dependent variable. In the third column, the estimated logit coefficients of the interaction terms between the post-auction time dummy variables and LOSE (from $LOSE \times T + 1$ to $LOSE \times T + 3$) stayed negative and statistically significant at the 0.01 significance level. The estimated AME reported in the last column indicates that LOSE group firms became a maximum of 3.9% points less likely to file patents having technological overlap with Nortel patents in the second year after the auction, as compared to the WIN group firms. However, this impact disappeared in the fourth year after the auction.

Placebo test

I examined how specific the findings were in relation to the timing of the auction event using a placebo test, where I set December 31, 2007, as the date of the placebo auction. Patents that were filed by the auction bidders in 2007, which were taken from the sample of patents filed by the bidders between January 1, 2004, and December 31, 2010, become the reference group. The data were fit to the same econometric specifications as in the main regression.

Table 2.6 presents the test results. The first two columns report the regression results with Comm Tech as the dependent variable. The interaction terms between the post-auction time dummy variables and LOSE (from $LOSE \times T + 1$ to $LOSE \times T + 3$) are statistically insignificant at the 0.1 significance level.

The last two columns report the placebo test with **Tech Overlap** as the dependent variable. All the interaction terms between time dummy variables and LOSE are statistically insignificant at the 0.1 significance level. Thus, there is no evidence for the existence of substantial changes in the relative likelihood of filing patents that have technological overlap with the Nortel patents after the placebo auction.

Table 2.6: Placebo Test

	DV:Comm Tech		DV: Tech Overlap	
	Logit(Comm tech)	AME(Comm tech)	Log(Tech over)	AME(Tech over)
LOSExT-3	0.0167	0.00257	0.228	0.0196
	(0.181)	(0.0279)	(0.175)	(0.0170)
LOSExT-2	0.252	0.0388	0.170	0.0146
	(0.175)	(0.0309)	(0.141)	(0.0134)
LOSExT-1	0.0894	0.0138	0.182	0.0157
	(0.211)	(0.0345)	(0.144)	(0.0138)
LOSExT+1	0.0815	0.0125	-0.0345	-0.00297
	(0.126)	(0.0200)	(0.353)	(0.0305)
LOSExT+2	0.0668	0.0103	0.269	0.0231
	(0.126)	(0.0183)	(0.354)	(0.0320)
LOSExT+3	0.0322	0.00496	0.0864	0.00742
	(0.166)	(0.0246)	(0.208)	(0.0184)
T-3	-0.133*	-0.0205	-0.137	-0.0118
	(0.0701)	(0.0148)	(0.171)	(0.0159)
T-2	-0.284***	-0.0437*	-0.217	-0.0186
	(0.105)	(0.0248)	(0.141)	(0.0137)
T-1	-0.0793	-0.0122	-0.0678	-0.00583
	(0.171)	(0.0290)	(0.142)	(0.0128)
T+2	-0.126	-0.0194	-0.0803	-0.00690
	(0.114)	(0.0183)	(0.0921)	(0.00721)
T+2	0.141	0.0216	-0.0826	-0.00710
	(0.0884)	(0.0182)	(0.251)	(0.0223)
T+3	0.0772	0.0119	-0.0884	-0.00760
	(0.153)	(0.0261)	(0.161)	(0.0146)
LOSE	0.0655	0.0101	0.262	0.0225
	(0.579)	(0.0874)	(0.339)	(0.0272)
Constant	-1.437***		-2.294***	
	(0.514)		(0.306)	
Pseudo R^2	0.003		0.006	
Observations	30177	30177	30177	30177

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Cluster robust standard errors in parentheses

Bootstrap standard error

The data consists of patents filed by five firms, which were regrouped into WIN and LOSE. Because the number of patents filed was heterogeneous across firms, while data points were nested at a firm level, estimation without considering this heterogeneity could lead to a bias toward firms that have filed a larger number of patents than the other firms. If so, the findings from the baseline regression may only reflect change in the innovative activities of specific firms who filed a larger number of patents. One way of resolving this problem is to use a bootstrap cluster SE estimation method (cluster at firm level) (See Duflo et al., 2011). To use this method, I reran the regression analysis using a firm-level cluster bootstrap SE with replacement allowed for 1,000 resampling.

Table 2.7: Estimation with bootstrap cluster standard error

	Logit(Comm Tech)	AME(Comm Tech)	Logit(Tech Overlap)	AME(Tech Overlap)
LOSEXT-4	0.0412	0.00713	0.0792	0.00635
	(0.271)	(0.0475)	(0.267)	(0.0211)
LOSEXT-3	0.220	0.0381	-0.0335	-0.00268
	(0.248)	(0.0446)	(0.291)	(0.0235)
LOSEXT-2	0.0911	0.0158	-0.132	-0.0106
	(0.224)	(0.0406)	(0.300)	(0.0245)
LOSEXT-1	0.00709	0.00123	-0.0203	-0.00162
	(0.130)	(0.0225)	(0.110)	(0.00877)
LOSEXT+1	-0.493***	-0.0855***	-0.0953**	-0.00764*
	(0.180)	(0.0263)	(0.0469)	(0.00434)
LOSEXT+2	-0.319	-0.0553*	-0.481*	-0.0386*
	(0.207)	(0.0329)	(0.249)	(0.0211)
LOSEXT+3	-0.127	-0.0220	-0.455*	-0.0365*
	(0.217)	(0.0342)	(0.267)	(0.0207)
LOSEXT+4	-0.0728	-0.0126	-0.364	-0.0292
	(0.287)	(0.0481)	(0.432)	(0.0333)
T-4	-0.0541	-0.00937	0.237	0.0190
	(0.188)	(0.0333)	(0.177)	(0.0158)
T-3	-0.205	-0.0356	0.171	0.0137
	(0.190)	(0.0334)	(0.237)	(0.0201)
T-2	-0.0504	-0.00874	0.246	0.0197
	(0.143)	(0.0256)	(0.154)	(0.0135)
T-1	0.0889*	0.0154	0.414***	0.0332***
	(0.0484)	(0.0108)	(0.0959)	(0.00585)
T+1	0.268***	0.0465***	0.242***	0.0194***
	(0.0787)	(0.0105)	(0.0424)	(0.00494)
T+2	0.447***	0.0775***	0.210	0.0169
	(0.165)	(0.0180)	(0.243)	(0.0200)
T+3	0.553**	0.0959***	0.124	0.00998
	(0.217)	(0.0247)	(0.243)	(0.0192)
T+4	0.614**	0.106***	-0.00882	-0.000707
	(0.280)	(0.0348)	(0.401)	(0.0322)
LOSE	-0.0278	-0.00482	0.371**	0.0297***
	(0.726)	(0.126)	(0.165)	(0.0114)
Constant	-1.355**		-2.600***	
	(0.644)		(0.154)	
Pseudo R^2	0.010		0.006	
Observations	42871	42871	42871	42871

Bootstrap cluster robust standard errors in parentheses (Resampling size, N=1000)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7 presents the estimation results. The coefficients of interaction terms between the pre-auction time dummy variables and LOSE are statistically insignificant at the 0.1 significance level. This indicates that the assumption of a pre-treatment parallel time trend of outcome variable for LOSE and WIN empirically holds. The estimated coefficients and statistical significance of the interaction terms between post-auction time dummy variables and LOSE indicate that the regression result is largely consistent with the main regression result.

2.5.4 Exploring Alternative Explanations

Self-selection

One may argue that the LOSE firms bid less for the Nortel patents than the WIN group because the LOSE group valued the Nortel patents less than the WIN group did in the first place. This difference could lead to the LOSE group's less active patenting activities related to Nortel patent relevant technologies. If so, the present study's findings would be a mere consequence of self-selection rather than the result of patent acquisition by the WIN group firms. However, the data does not support this argument. First, if this alternative argument was credible, substantially decreased patenting activity by the LOSE group on technologies relevant to the Nortel patents would be expected to persist over time. My analysis clearly shows that the LOSE group's patenting activity bounced back sharply from the second or third year after the auction, and the recovery seems to continue afterward. Second, the LOSE group firms do not seem to value the Nortel patents less than the WIN group given that the LOSE group's patenting activity on Nortel patent relevant technology was not lower than that of the WIN group just before the auction. As can be seen in 2.3, the coefficients of LOSE are either statistically insignificant or even positive. This indicates that the LOSE group's patenting activity of Nortel patent relevant technology just before the auction was not less than or even greater than that of the WIN group.

An unobserved event may have occurred to LOSE-group firms after the auction

The findings of this study could simply be caused by unobserved events during the post-auction period that are irrelevant to the Nortel patent auction. If such an event influenced the LOSE group firms' patenting activities and R&D outcomes related to communications technologies in general, the present study's findings might not represent a causal impact of the Nortel patent auction.

To rule out this alternative explanation, I designed a crucial test that examined the specificity of the findings to the Nortel patents as opposed to patents that were filed by a firm comparable to Nortel. If this competing explanation was credible, similar findings to those of the main regression results should be observed when examining the LOSE group firms' likelihood of filing patents that technologically overlap with patents filed by the Nortel comparable firm.

For this test, I employed Qualcomm as the alternative to Nortel, with the patents matched by patent application year and NBER subclass. I chose Qualcomm because, like Nortel, they were not in market competition with the auction participants in the smart device market while they were intensively developing communications technologies (Kang and Motohashi, 2015). Indeed, Qualcomm has been a member of various telecommunications standard-setting organizations, such as ETSI, as was Nortel.[5]

Using the replacement-allowed and one-to-one matching procedure, 1,366 Qualcomm patents were selected as the alternative set to Nortel patents. Then, I regenerated the three variables—**Tech Overlap**, **Direct Citation**, and **Shared Reference**—for each patent that was filed by the auction bidders, replacing the Nortel patents with the Qualcomm patents. If the findings obtained from the main regression were not specific to the Nortel patents but were, instead, the result of an irrelevant and unobserved event, I should have observed a decrease in the LOSE group firms' likelihood of filing patents during the post-auction period that technologically overlap with the Qualcomm patents. However, that was not the

[5] See `http://www.etsi.org/membership/current-members`

case.

Table 2.8: Test using the Qualcomm's patents

	DV:Tech Overlap		DV: Direct cite		DV: Same references	
	Logit(Tech over)	AME(Tech over)	Logit(Direct cite)	AME(Direct cite)	Logit(Same Ref)	AME(Same Ref)
LOSExT-4	0.0672	0.00839	1.279***	0.00746*	0.0624	0.00770
	(0.293)	(0.0365)	(0.371)	(0.00442)	(0.299)	(0.0369)
LOSExT-3	0.0705	0.00879	-0.240	-0.00140	0.0527	0.00651
	(0.266)	(0.0331)	(0.441)	(0.00301)	(0.274)	(0.0339)
LOSExT-2	-0.0357	-0.00445	0.847	0.00494	-0.0483	-0.00597
	(0.0569)	(0.00690)	(0.517)	(0.00407)	(0.0437)	(0.00549)
LOSExT-1	0.226*	0.0282	1.501***	0.00876***	0.218*	0.0269
	(0.119)	(0.0203)	(0.285)	(0.00234)	(0.116)	(0.0196)
LOSExT+1	-0.0209	-0.00261	-0.0700	-0.000409	-0.0272	-0.00336
	(0.162)	(0.0198)	(0.540)	(0.00311)	(0.153)	(0.0183)
LOSExT+2	-0.165	-0.0206	0.375	0.00219	-0.185	-0.0229
	(0.237)	(0.0255)	(0.403)	(0.00303)	(0.226)	(0.0233)
LOSExT+3	-0.137	-0.0171	0.279	0.00163	-0.161	-0.0199
	(0.336)	(0.0384)	(0.551)	(0.00378)	(0.334)	(0.0372)
LOSExT+4	-0.449	-0.0560	0.303	0.00177	-0.459	-0.0567
	(0.458)	(0.0465)	(0.947)	(0.00604)	(0.442)	(0.0438)
T-4	0.0930*	0.0116	-0.382	-0.00223	0.0850	0.0105
	(0.0559)	(0.00895)	(0.353)	(0.00275)	(0.0662)	(0.00995)
T-3	0.0313	0.00391	0.840*	0.00490	0.0343	0.00424
	(0.0917)	(0.0117)	(0.437)	(0.00419)	(0.0806)	(0.0104)
T-2	0.0954***	0.0119***	0.396	0.00231	0.0995***	0.0123***
	(0.0213)	(0.000603)	(0.487)	(0.00270)	(0.00658)	(0.00184)
T-1	0.144	0.0179*	-0.478**	-0.00279***	0.152	0.0187**
	(0.107)	(0.00968)	(0.200)	(0.000944)	(0.104)	(0.00905)
T+1	0.144	0.0180	0.174	0.00101	0.149	0.0184
	(0.162)	(0.0169)	(0.211)	(0.00130)	(0.152)	(0.0154)
T+2	-0.0156	-0.00194	-0.214	-0.00125	-0.00397	-0.000491
	(0.227)	(0.0287)	(0.394)	(0.00271)	(0.215)	(0.0266)
T+3	-0.0333	-0.00416	0.342	0.00200	-0.0260	-0.00321
	(0.336)	(0.0427)	(0.525)	(0.00244)	(0.333)	(0.0418)
T+4	-0.0439	-0.00548	0.0183	0.000107	-0.0366	-0.00452
	(0.457)	(0.0581)	(0.785)	(0.00456)	(0.441)	(0.0553)
LOSE	0.599	0.0747	-0.252	-0.00147	0.615	0.0759
	(0.650)	(0.0659)	(0.685)	(0.00444)	(0.645)	(0.0641)
Constant	-2.050***		-5.314***		-2.070***	
	(0.650)		(0.662)		(0.645)	
Pseudo R^2	0.013		0.014		0.013	
Observations	42871	42871	42871	42871	42871	42871

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Cluster robust standard errors in parentheses

Table 2.8 displays the results. The interaction terms between post-auction time dummy variables and LOSE are statistically insignificant at the 0.1 level, which does not support the alternative explanation.

Patent or Invention?

Firms decide whether or not to file patents on already developed inventions. Thus, the findings of the present study could be the result of changes in patenting behavior by the LOSE group firms. More specifically, if, after the auction, the LOSE group decided not to file patents related to the Nortel patents, even if they had already developed technologies relevant to the Nortel patents before the auction, the findings of the present research may not indicate changed innovative activities of the LOSE group firms but, rather, simply show changed "patenting behavior."

One possible explanation is that a rival's acquisition of the Nortel patents might have marginalized the utility of having a patent for an invention relevant to the Nortel patents for the LOSE group. For example, the LOSE group firms might have developed inventions related to the Nortel patents well before the auction, so that patenting such inventions could have been strategically beneficial if the LOSE group could obtain the Nortel patents. However, because the WIN group acquired the Nortel patents, there might have been less incentive to file patents on such inventions for the LOSE group.

To test the credibility of this alternative explanation, I conducted a crucial test by utilizing the continuation patent application practice in the US patent system. In the United States, a patent applicant can amend or add new patent claims to a previous patent by filing so-called children patent applications as long as the previous patent application is not abandoned. By doing so, the patentee can extend the scope of protection of the patented invention ex-post facto. I considered the LOSE group's patents that were filed before the auction and categorized as communications or that have technological overlap with the Nortel patents to be a body of inventions related to the Nortel patents that were developed before the auction. Then, I examined how many children applications of these patents were filed each year after the auction. If the suggested alternative explanation was credible, I would have been likely to observe that the LOSE group firms filed fewer children applications in the years after the auction than in preceding years.

First, I selected two groups of patents that were filed by the LOSE group before the auction. One group comprised patents that were filed between July 1, 2006, and June 30, 2007. Another group comprised patents that were filed between July 1, 2008, and June 30, 2009. For the first group of patents, I supposed that a hypothetical auction occurred on June 30, 2009. Then, I counted the number of children patent applications filed in the time period of three years before the hypothetical auction date to two years after it, so from July 1, 2009, to June 30, 2011. Because the period of observation does not contain the post-Nortel auction period (beginning June 30, 2011), the first group of patents became the control group. For the second group of patents, I examined the number of children patent applications beginning three years before Nortel's auction and filed every year thereafter until two years after the auction ended (on June 30, 2011). Because the period of observation for this group contains the genuine post-auction period, this group of patents became the treatment group. If this competing explanation is supported, the number of children patent applications for the treatment group should have dropped after the auction compared to the control group. With this setting, the two-year post-auction period became the post-treatment period. Figure 2.5 illustrates this crucial test design.

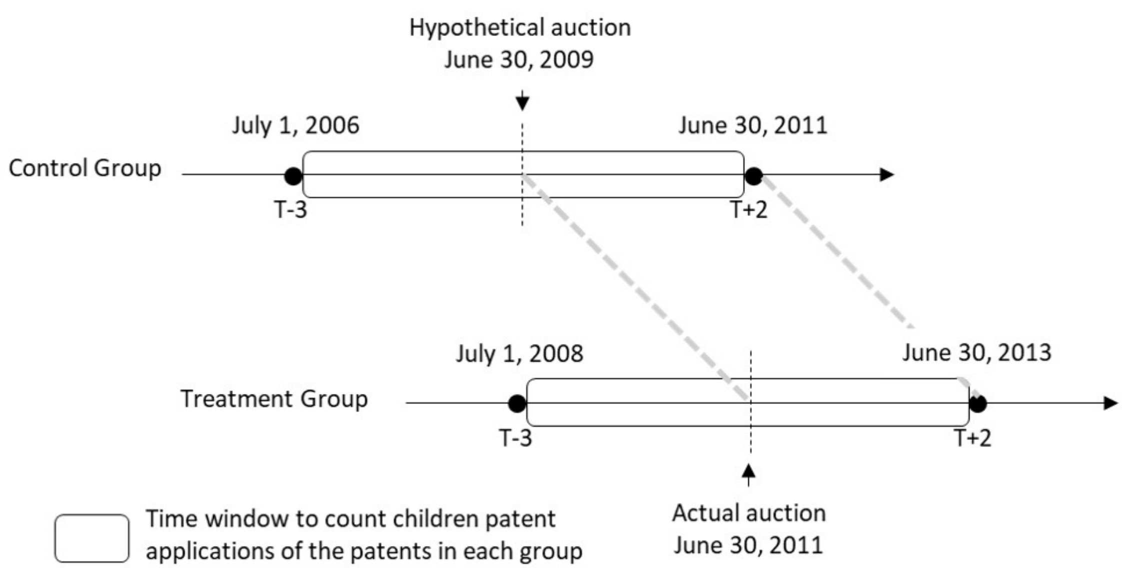


Figure 2.5: Crucial test design with Continuation Patent Application Data

I retrieved information about continuation patent applications of the Nortel patents (i.e., continuation, continuation-in-part, divisional patents) from the USPTO's Patent Examination Research Dataset.[6] Based on these data, I identified the children patent applications for the two selected groups of patents. Then, the yearly patent panel data was constructed with the number of children patent applications associated with a patent in the dataset as the dependent variable. I utilized the panel data DiD approach for the analysis. The number of children patent applications for patents that were filed within the year before the auction became the reference group. To additionally examine the change in the likelihood of filing the continuation applications, I also regressed the dummy variable that took the value of 1 if there was any type of children patent application to the patent of interest in the corresponding time window. Table 2.9 reports the regression results.

The first two columns report the ordinary least squares (OLS) regression results using the number of continuation patent applications as the dependent variable. The interaction terms between the dummy variable for the treatment group (**Treat**) and post-auction time dummy variables ($Treat \times T+1$ and $Treat \times T+2$) is statistically insignificant at the 0.1 significance level. The analysis result using a dummy variable that takes the value of 1 if there was at least one child patent application to the patent of interest in the corresponding time window is reported in the third and fourth columns. The coefficients of $Treat \times T+1$ and $Treat \times T+2$ are statistically insignificant at the 0.1 significance level.

Winner's Effect?

In the main regression, I considered the counterfactual of the LOSE group's post-auction R&D outcomes as those of the WIN group. However, this research design may not be able to properly identify the impact of the auction on the LOSE group's innovative activities because the auction result could also affect the auction-winning firms' R&D outcomes. After the WIN group acquired the Nortel patents, they could have engaged in more development

[6] Available at `https://bulkdata.uspto.gov/data/patent/pair/economics/2016/`

Table 2.9: Crucial test using continuation patent applications (OLS)

	N. of children apps	N. of children apps	Exist children apps	Exist children apps
TreatxT-2	-0.0576**	-0.0348	-0.0478*	-0.0348
	(0.0281)	(0.0345)	(0.0245)	(0.0345)
TreatxT-1	-0.0172	-0.0403	-0.00873	-0.0403
	(0.0481)	(0.0594)	(0.0458)	(0.0594)
TreatxT+1	0.0270	0.0788	0.0367	0.0414
	(0.0299)	(0.0548)	(0.0265)	(0.0386)
TreatxT+2	0.00321	0.0142	0.0129	0.0215
	(0.0328)	(0.0517)	(0.0296)	(0.0446)
T-2	0.0576***	0.0722***	0.0576***	0.0722***
	(0.0149)	(0.0224)	(0.0149)	(0.0224)
T-1	0.284***	0.283***	0.281***	0.283***
	(0.0281)	(0.0355)	(0.0275)	(0.0355)
T+1	0.0216**	0.0333*	0.0216**	0.0333*
	(0.0101)	(0.0175)	(0.0101)	(0.0175)
T+2	0.0647***	0.117***	0.0647***	0.100***
	(0.0157)	(0.0328)	(0.0157)	(0.0251)
Patent FE	YES	YES	YES	YES
Constant	0.0248***	0.0174	0.0207***	0.0174*
	(0.00878)	(0.0107)	(0.00748)	(0.00999)
R^2	0.125	0.085	0.130	0.104
Adjusted R^2	0.122	0.079	0.127	0.099
Sample	Comm Tech	Tech Overlap	Comm Tech	Tech Overlap
Observations	2420	1435	2420	1435

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of Nortel patent relevant technologies. As a result, the DiD estimators under the current research design could indicate that the WIN group firms were encouraged to focus on inventions of technologies relevant to the Nortel patents as opposed to the LOSE group's firms being deterred from developing technologies relevant to the Nortel patents.

To check the credibility of this alternative explanation, I analyzed only the likelihood of the LOSE group firms filing communications patents and patents that have technological overlap with the Nortel patents. Because the acquisition of the Nortel patents by the WIN group can be considered an exogenous event from the LOSE group's perspective, this analysis can be helpful for isolation of the impact of the patent transfer on the LOSE group's innovative activities. Figure 2.6 visualizes the regression results.

The results indicate that, after the auction, the LOSE group's likelihood of filing com-

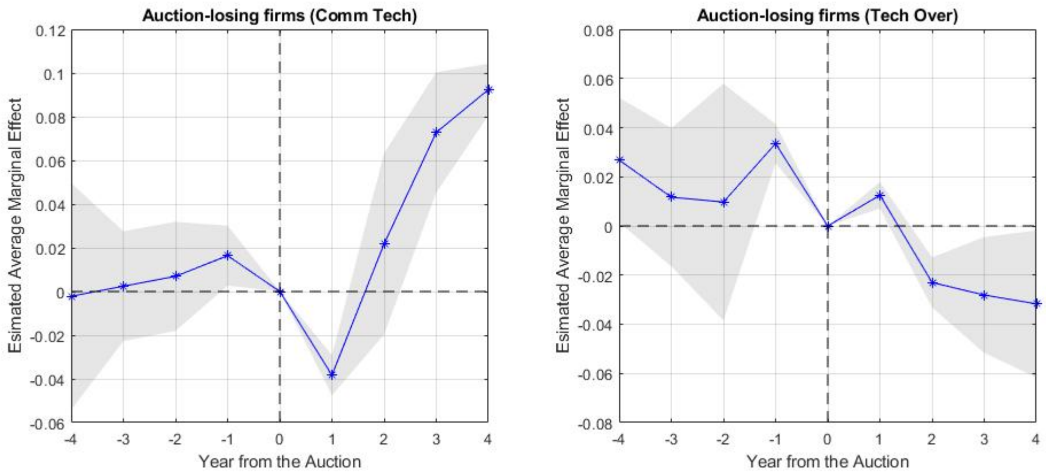


Figure 2.6: Auction-losing firms' likelihood of filing Comm Tech and Tech Over

munications patents and patents that have technological overlap with the Nortel patents dropped significantly after one or two year(s) the auction. The result of this analysis implies that the LOSE group's innovative activities around technologies relevant to the Nortel patents have decreased since the WIN group's acquisition of the Nortel patents.

2.5.5 Evidence from Post-auction Events

In 2013, Google and other smartphone manufacturers that employ the Android operating system were sued by Rockstar for alleged infringement on seven of Nortel's auctioned patents. Most of the lawsuits were settled in 2014.

Intel has not been sued for infringement of the Nortel patents after the auction. Instead, the reported cost for the acquisition of patent licenses given in their 10-K documents, shown in Figure 2.7, indicate that Intel spent $810 million in 2012, which is an unusual expenditure for the acquisition of patent licenses.[7] Even after considering the large-scale license agreement with Interdigital in 2012, this expenditure is still extraordinarily high.[8] Considering 2012 was one year after the Nortel patent auction and that the average expenditure for

[7] Data obtained from `http://www.sec.gov`.

[8] Intel and Interdigital made a $357 million scale license deal in 2012 (see `https://newsroom.intel.com/newsreleases/interdigital-agrees-to-375-million-patent-transaction-with-intel/`).

the acquisition of patents and licenses for Intel had been $81 million per year, this finding suggests that Intel faced greater costs for the acquisition of patent licenses after the Nortel patent auction.

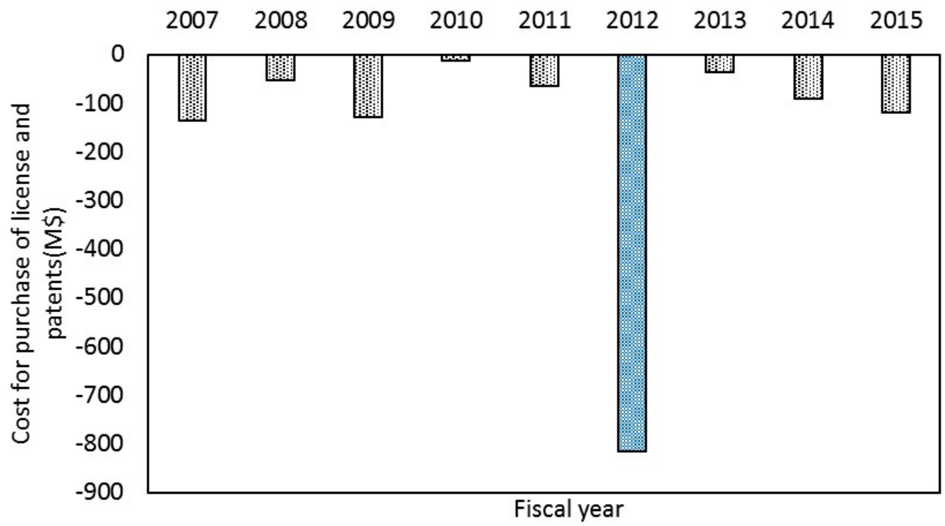


Figure 2.7: Intel's cost for purchase of license and patents reported in 10Ks

Given that an imposed patent holdup risk often results in either patent infringement disputes or substantially increased costs for patent licensing, the described post-auction events seem to reasonably explain how the result of the Nortel patent auction imposed a greater level of patent holdup risk to the LOSE group firms.

2.6 Discussion

This study sheds theoretical and empirical light on how a firm's acquisition of external patents affects rival firms' innovative activities.

The constructed model demonstrated that a firm can earn more market profit by imposing a greater patent holdup risk on rivals through the purchase of a patent that could be critical for the rival's market operations. The constructed model rationalized that if a firm's patent purchase imposes a greater risk of ex-post patent holdup on its rival, the rival firm becomes less active in developing technologies related to the patent purchased by the focal firm.

I empirically analyzed the case of Nortel's patent auction in 2011 to test the derived prediction. According to the hypothesis derived from the constructed model, the auction-losing firms should have become less active in developing technologies related to the Nortel patents, and the analysis found empirical evidence supporting this hypothesis.

However, this impact did not persist for long. Although the auction-losing firms were deterred from developing technologies relevant to the Nortel patents immediately after the auction, these firms' development of such technologies recovered a few years later.

I explained my finding by referencing firms' post-auction efforts to cope with the increased risk of an ex-post patent holdup. Immediately after the Nortel patent auction, Google announced that it planned to acquire Motorola Mobility.[9] Given that Motorola Mobility owned a sizable patent portfolio of communications technology, Google's acquisition announcement was believed to be a strategic response to its increased risk of the ex-post patent holdup created by their rival firms' acquisition of the Nortel patents. Intel also made an effort to acquire external patents of communications technologies after the auction. For instance, in 2014, Intel announced that it would purchase about 1,400 telecommunications patents from Prowave Inc. These post-auction actions taken by Google and Intel can be understood to be part of a so-called working solution (Walsh et al., 2003).

The concept of working solutions and the findings of the present paper jointly explain why there is mixed evidence for detrimental impacts of patent holdup on firms' innovative activities. Firms seek ways to cope with the increased risk as time goes by, and in doing so, the detrimental impact of the patent holdup on the firms' innovative activities is gradually mitigated.

Does this finding imply that we do not need to be concerned about the long-term effects of a firm's patent purchase on rival firms' innovative activities because the impact will be mitigated spontaneously as the affected firms equip themselves with working solutions?

[9] Actual patent ownership transfer occurred in 2014, and Google resold Motorola Mobility to Lenovo in the same year.

My findings do not allow for drawing this conclusion because not all firms will be capable of building and executing working solutions. Firms having sufficient resources and the capability to build working solutions will be able to effectively cope with the effects on their innovative activities of another firm's patent purchase. However, if firms are small or medium-sized enterprises, which often lack resources, they may have difficulties building a working solution, in which case the impact could be long-lasting and critical for them. Accordingly, when interested parties, such as innovation/patent policymakers, examine how a firm's patent purchase for strategic benefit affects innovation, it is essential to consider who the rival firms are and whether they are capable of formulating a strategy for coping with the probable patent holdup resulting from a patent purchase by the focal firm.

Some may argue that LOSE group firms could be protected from the detrimental impacts of auction results under the fair, reasonable, and non-discriminatory (FRAND) regime, even if the WIN group tried to utilize the LOSE group's patent holdup risk. If the FRAND regime worked, LOSE group firms should not have been affected by the auction result.

However, the FRAND regime is vague to enforce practically (Layne-Farrar et al., 2007; Craig, 2013; Larouche et al., 2014). In practice, the benchmark royalty that is essential for determining whether proposed patent licensing terms on the negotiation table are "fair, reasonable, and non-discriminatory" is often not observable because there is no incentive or legal requirement that mandates a firm's disclosure of their historical licensing terms in detail. In the absence of such a benchmark, licensing negotiations under FRAND tend to result in legal disputes. Given this limitation, the utilization of FRAND might not be as effective as was intended.

2.7 Conclusion

The primary implication of the present study is that the market for patents is of a different nature than the market for technology. In the market for patents, firms may acquire external patents so they can strategically exploit their patent exclusion rights over their market competitors, which may increase ex-post patent holdup risk for these rival firms, consequently increasing their innovation costs. On the other hand, the subjects of transactions in the technology market are technological ideas. Technology transactions promote innovative division of labor and the efficient allocation of technology to those who can do a better job at commercializing it.

This different natures of the market for patents and the market for technology forces us to reconsider policies that aim at encouraging patent ownership transactions in the belief that an active patent market will bring the benefits of the technology market to innovation. But this assumption needs careful reconsideration. We need to more thoroughly examine questions such as, when does active patent ownership transfer actually promote innovation? When does it generate patent holdup and unnecessary cost for innovation?

This study contributes to extending our understanding of the relationship between patents and innovation. Studies have conventionally discussed whether patents promote or hamper innovation, focusing on the tension between technological monopoly and incentives for innovation conferred by the patent system (e.g., Arrow, 1962; Nordhaus, 1969). In trying to understand how the existence of a patent shapes innovation, the present study untangles part of the puzzling relationship between patents and innovation by emphasizing the importance of taking into consideration who owns which patents and whether the patentee is willing to use a patent for strategic purposes.

Firms can also benefit from the present study. The finding that a firm's patent purchase affects its rival's innovative outcomes suggests that firms need to carefully monitor rivals' patenting activities. But they also need to monitor what patents are purchased by rival firms and examine whether such patents can impose a holdup risk against their innovative activities and business operations so they can build a more effective intellectual property strategy.

The findings in this study by no means imply that patent transfer does not serve as a channel for technology transactions or that it only impedes innovation. The data and findings of this study do not allow such conclusions to be drawn. Whether patent transfer for strategic exploitation of the patent exclusion right generates more social costs than benefits and how it affects overall innovation are remaining questions.

Like all research, this study is not without limitations. First, I have measured outcomes of innovative activities of firms through their patenting activities. However, as many studies have pointed out, patents are not always a reliable proxy for firms' innovative activities. Not all inventions are patented (Cohen et al., 2000; Moser, 2012). Patents used to be filed for strategic purposes (e.g., Ziedonis, 2004; Motohashi, 2008), and there are many reasons other than R&D for filing patents (see, Cohen et al., 2000; Graham et al., 2009; Morton and Shapiro, 2014). Future studies may address this limitation by using alternative measures.

Second, although analyzing the case of Nortel's patent auction was useful for identifying the impact of patent ownership transfer, the conclusion drawn from this case is subject to external validity issues because the finding is based on a single case. I hope future studies can bring more cases and add more insights to the conclusions of the present study.

Finally, the present study did not consider the role of regulatory authorities. When it comes to Nortel's patent auction, the redistribution of the patents to the three member-companies of a consortium was the subject of sanctions by the US Department of Justice (DoJ) because of the concern that the redistribution of patents might harm market competition. In 2012, the DoJ permitted the acquisition of the patents by the three member-companies but forced them to not exploit the patents opportunistically.[10] While how the DoJ's post-auction actions might have influenced the bidding firms' R&D activities with respect to the Nortel patents is not clear, it is worthy of further investigation.

[10] See `https://www.justice.gov/opa/pr/statement-department-justice-s-antitrust-division-its-decision-close-its-investigations.`

CHAPTER 3
HOW DOES ANTITRUST REGULATION OF PATENTS CONSOLIDATION AFFECT FOLLOW-ON INNOVATION?

One of the prominent questions across the patent and antitrust policy domains is whether the antitrust intervention into a formation of patent monopoly promotes or discourages innovation.

This study aims to help answers this question by examining the short-term effect of antitrust regulation of the creation of the patent monopoly on the rate of follow-on innovation. I identify the formation of the patent monopoly with a firm's consolidation of existing patents. By building a simple analytical model, I explore how the creation of a patent monopoly through a firm's patents consolidation affects the rate of follow-on innovation. The model shows that, in a sector where cumulative innovation is crucial, a firm's consolidation of patents on substituting upstream technologies for what it possesses negatively affects the rate of follow-on innovation of its market competitor. The regulation of patent consolidation, in this case, is predicted to positively affect competitors' development of the follow-on innovation.

I test the derived prediction by using the case of the US Department of Justice's (DoJ) partial regulation of Novell's software patents sales to four large proprietary software companies (Microsoft, Oracle, EMC, and Apple) in 2011, while considering patentable invention as an proxy for technological innovation. My analysis shows that the antitrust regulation positively affected the development of follow-on inventions by firms that were in market competition with the patent consolidators. A series of falsification of alternative explanations indicates that the antitrust regulation mitigated the negative impact of patent monopoly formation on these firms' development of follow-on inventions.

3.1 Introduction

"The aims and objectives of patent and antitrust laws may seem [...] wholly at odds. However, the two bodies of law are actually complementary, as both are aimed at encouraging innovation, industry and competition" (Atari Games Corp. v. Nintendo of America, Inc., 897 F.2d 1572, 1576 (Federal Circuit, 1990)).

"Intellectual property rights do not necessarily [...] create monopolies because consumers may be able to substitute other technologies [...] for the protected technologies. Consequently, antitrust and intellectual property are properly perceived as complementary bodies of law that work together to bring innovation to consumers" (DoJ and FTC, 2007).

Although both patent and antitrust laws aim to enhance social welfare, their efforts to do so have been perceived as being in conflict with one another. The patent law allows a temporal monopoly on technological idea in order to incentivize innovation. In contrast, antitrust law restricts monopolistic market powers in order to promotes competition. To this conventional point of view, the modern policy understanding suggests that the two institutions are not conflicted, but rather compatible. The mere existence of a patent does not form the monopoly because innovators can access substitutes for the patented technology, while the patent law protects innovators' appropriability (DoJ and FTC, 2007). Accordingly, the patent promotes both of market competition and innovation (Gilbert and Shapiro, 1996).

This thought seems to accommodate proponents' views of patent and antitrust laws. However, it does not fully address the key question of how the institutional tension between the two bodies of law shapes innovation (See Oppenheim, 1955). The compatibility between the two institutions is conditioned on which innovators can access substitutes for patented technology. What if a firm comes to own most existing patents and, hence, effectively form a patent monopoly? Will the antitrust regulation of such patents consolidation by a few firms encourage or discourage innovation? Although this inquiry takes a crucial part in describing how the two institutions interact for innovation and relate to another long-standing question of whether a stronger (or weaker) patent protection encourages innovation (e.g., Kortum and Lerner, 1998; Sakakibara and Branstetter, 2001; Hall and Ziedonis, 2001; Lerner, 2002), relevant studies seem to have limitations in providing the direct answer.

First, whether innovators' monopolistic profit drives innovation is inconclusive. Schumpeter (1942) theorized that market concentration (weak competition) promotes innovation; subsequent studies found further supportive empirical evidence (e.g., Blundell et al., 1999; Greenhalgh and Rogers, 2006). In contrast, Arrow (1962) claimed that competitive market environment spurs innovation and empirical research has supported this claim (e.g., Schor, 2004; Correa and Ornaghi, 2014). Aghion and Griffith (2005)'s study is positioned between the two opposing ends to show that an inverted U-shape relationship exists between the intensity of market competition and the rate of innovation. This inconclusiveness may be due to the endogenous relationship between market competition and innovation (Sidak and Teece, 2009).

Second, the net effect of patent protection on innovation is an ongoing research question. Exclusive access to certain knowledge through patenting may deter innovation by preventing innovators from accessing essential technological inputs for another innovation (e.g., Heller and Eisenberg, 1998; Shapiro, 2000; Jaffe and Lerner, 2011). Meanwhile, if the monopolistic profit of an original innovator is not protected, the incentive for the private R&D investment is deprived, and less innovation than the socially desirable level can be created as a result.

Third, how the antitrust authority's regulation of the formation of patent monopoly affects innovation has been less examined. The studies on the antitrust authority's role in a patent system has focused on shaping the patent system by finding the optimal length or breadth of patent right (Gilbert and Shapiro, 1990; Klemperer, 1990; Denicolo, 1996) and examining the consequence of restricting the exertion of patent right for market competition and consumer welfare (e.g., Chang, 1995; Gilbert and Shapiro, 1996; Jaffe, 2000), with less interest in innovation (Khan, 2016).

How does the antitrust regulation of patent-monopoly formation affect innovation? The present study aims to answer this question in part by examining the short-term effect of the antitrust regulation of formation of patent monopoly on the rate of follow-on innovation. The patent monopoly can be created through patents consolidation in two ways. One is a preemptive patenting by internal Research and Development (R&D). The preemptive patenting helps maintaining monopolistic market power of market dominant players (Gilbert and Newbery, 1982), yet this does not violate the antitrust law (See Gilbert, 1987). Another is by aggregating existing patents through patents transfer. The patents consolidation by patents transfer can lead to not only restriction to an upstream technology by downstream innovators (Hahn, 1984; Figueroa and Serrano, 2013) but also deterring their market entry (See Ziedonis, 2004; Gotts and Sher, 2012), which may result in antitrust law violation. The present study focuses on the later case.

I start by building an analytical model that illustrates how the downstream market competition and follow-on innovation are affected by a firm's aggregation of existing patents. The model predicts that, in a sector where innovation is created cumulatively, a firm's patents consolidation negatively affects the rate of its market competitors' follow-on innovation, only if the patent-acquiring firm amasses patents on substituting upstream technologies for what it already owned (i.e., consolidation of patents on substituting technologies). However, the formation of such a patent monopoly does not affect the rate of the patent consolidator's follow-on innovation activity. In this case, the regulation of patent-monopoly formation by preventing patent consolidation is predicted to positively affect the rate of follow-on innovation by the market competitors of the patent-consolidating firm while not affecting this firm's development of the follow-on innovation.

I empirically test this prediction by capitalizing on the case of the US DoJ's intervention into Novell's (an open-source software company) sale of Linux-related patents to four large proprietary software companies (i.e., Microsoft, Oracle, EMC, Apple). In the analysis, I use a patented invention as the proxy for an innovation. For a antitrust concern, the US DoJ stepped into this patent transfer deal. The intervention was a partial regulation of the transfer of Novell patents to Microsoft. As a result, only part of the Novell's patents could be transferred to the other three software companies. Because the DoJ's regulation was triggered by the German Antitrust Authority's disclosure of information about the patent buyers, followed by Open Source Software (OSS) advocate's objection to this deal, I argue that the DoJ's intervention was an exogenous event in this case. Using the patent citation count as a proxy for the number of follow-on inventions, I compare the rate of follow-on inventions for the transfer-regulated patents and transferred-patents after the DoJ's intervention.

My analysis using the Difference-in-Difference (DiD) and synthetic control approach with a series of falsification of alternative explanations supports the derived prediction. The antitrust regulation of consolidation of Novell's patents positively affected the development of the patent-consolidating firm's competitors' follow-on inventions. However, no evidence indicates that the regulation affected the rate of patent-consolidating firms' follow-on inventions.

The contribution of the present study is threefold. First, this study advances the broad policy discussion about the interaction between antitrust and patent laws regarding innovation by examining the impact of antitrust regulations of patent-monopoly on follow-on innovation. Second, the findings of the present study highlight the importance of governmental attention to patent-only transfer with respect to its impact on innovation. Conventionally, the antitrust authority has focused on regulating business deals such as Mergers and Acquisition that may harm market competition. This study suggests that antitrust authorities also need to pay closer attention to patents-only transfer deal for innovation. Finally, the present study advances the recent policy discourse on how the market for patents shapes innovation by extending the scope of the discussion from patent transfers for ex-post patent enforcement (FTC, 2011) to the creation of patent-monopoly.

The remainder of this paper is structured as follows. Section 2 reviews the background of this study. Section 3 describes the model that illustrates whether and how patent transfer creates a patent monopoly and its impact on the rate of follow-on innovation. Section 4 describes the data and method for the empirical analysis. Section 5 presents the findings, and the implications are discussed in Section 6.

3.2 Background

3.2.1 Patent Transfer, Antitrust Law, and Innovation

Firms transfer patents for various reasons. Firms sell patents for asset monetization (Kelley, 2011; Orr, 2013; Morton and Shapiro, 2014; Serrano and Ziedonis, 2018) or financing through patents collateral (Hochberg et al., 2018).

Meanwhile, firms may purchase patents for defensive purposes (Lemley et al., 2016). A well-organized patent portfolio can be a useful bargaining chip in business negotiations (Cohen and Lemley, 2001; Hall and Ziedonis, 2001; Ziedonis, 2004). Specifically, when a firm is sued for patent infringements, the firm can use owning patents to settle the dispute through cross-licensing. Because this strategy becomes feasible when the firm has a sufficiently strong patent portfolio (Von Graevenitz et al., 2013), the firm has an incentive for acquiring patents from outside to strengthen their patent portfolios.

Firms also purchase patents to raise their rivals' operating cost. The first essay of this dissertation shows that firms have an incentive to purchase patents to leverage market competitor's ex-post patent holdup risk, and doing so effectively increases the rival's operating cost while making the market competitors less active in developing the relevant technologies to the patents.

Firms' patents transfer increasingly gains the attention of antitrust and innovation policymakers for its associated antitrust issue and less clear consequence for innovation.

On the one hand, the patent transfer may facilitate efficient reallocation of patents to those who can utilize the patents better (Galasso et al., 2013; Akcigit et al., 2016) while promoting innovators' specialization in developing ideas (Lamoreaux and Sokoloff, 1999). For firms, the patent transfer can be a useful instrument in managing their intellectual property (IP) assets. The flexible IP management enabled by trading patents may help firms to make more efficient R&D investments. In addition to the firms' patents transfer activity, the government can contribute to promoting innovation while encouraging the knowledge diffusion by purchasing patents from inventors and sharing them in public domain (Kremer, 1998).

On the other hand, the patent transfer can harm market competition by allowing a few firms to amass patents and thereby effectively monopolize the downstream market (Hahn, 1984; Figueroa and Serrano, 2013). For instance, a patent buyer can enjoy monopolistic market power by aggregating patents on particular upstream technology and by then restricting downstream innovators' access to these patents (Ziedonis, 2004; Gotts and Sher, 2012). In addition, the patent transfer can lead to frivolous patents infringement lawsuits by those who purchase patents to extract excessive rent from operating firms through ex-post patent enforcement. This can increase the cost of innovation and result in a sub-optimal R&D investment by those operating firms. For this issue, ex-post patent enforcement has become one of the agenda in a recent hearing held by FTC (2011).

For the probable antitrust issue, patents transfer can be the subject of authorities' regulation. In US, two legislative acts enable the regulation of patent transfer: The Sherman Act and The Clayton Act. The Sherman Antitrust Act (26 Stat. 209, 15 U.S.C. §§17) was enacted in 1890, to regulate unlawful market monopolies. This act enabled the regulation of business practices that may discourage market competition.

The Clayton Act was enacted in 1914 (38 Stat. 730, 15 U.S.C. §§1227, 29 U.S.C. §§5253) to specify which business practices violate the Sherman Act, elaborating on its antitrust enforcement scheme and its legal remedies. Section 7 of the Clayton Act provides the key foundation for the regulation of patent transfer. The section states that business practices that may harm market competition or lead to the formation of a monopoly can be regulated by authorities. Based on this section, the patent transfer that can harm market competition or form a monopoly can be subject to regulation (Klitzke, 1980; Gotts and Sher, 2012).

Gotts and Sher (2012) detail in what cases the regulation of patents transfer will be in consideration. In one case, the patent transfer can be regulated when it is likely to result in the exclusion of the patent buyer's competitors from the market. In another case, the patent transfer can also be regulated when it results in increased patent thicket and aggravation of patent holdup issue. In a third case, the patent transfer can be regulated when the patent buyer has different incentives in using the patents than the patent seller. For instance, if the patent buyer has a greater incentive to block market entry of competitors, while the patent seller had the intention to share the patents at reasonable royalty fee, the patent transaction can be subject to an antitrust investigation based on the possible violation of section 7 of The Clayton Act.

3.2.2 Open Source Software and Patents

A computer program (i.e., software) is implemented by writing source code and converting it into an executable form (i.e., a binary file). The source code is protected by copyright law.

Accessibility to the source code of the existing software is crucial for developing the new software because it is often built cumulatively (Cohen and Lemley, 2001; Smith and Mann, 2004; Bessen and Maskin, 2009; Hall and MacGarvie, 2010; Noel and Schankerman, 2013).

The software is categorized into two types based on public accessibility to the source code. One is proprietary software. Proprietary software is built by exclusive profit-seeking entities. The source code of the software is not provided to the third party. Instead, the software vendor provides a package of binary files which are executable on users' machines. Even if one could obtain the software's source code, one cannot modify the source code nor distribute the software that was built on it without the permission of the source code's original copyright holder.

The second type is OSS. The copyright holder of OSS makes the source code available to anyone who complies with a designated OSS license term. The recipients of the source code can freely modify, study, and distribute the implemented software as long as they comply with the given OSS license terms. GNU Public License (GPL) is one of the popular OSS license schemes. Linux is the computer operating system that complies with the GPL. Accordingly, anyone can freely use the GPL-licensed linux source code as long as comply with the GPL terms.

Free access to the software source code and its distribution made the Linux-based software a strong competitor to proprietary computer programs. The competition led major proprietary software companies to take actions for deterring Linux community's software development. Patents infringement disputes raised by Microsoft against Linux vendors in 2007[1] and the legal disputes between SCO-group and Linux vendors regarding copyright/patents infringement are the examples. Wen et al. (2013) showed that such patents enforcement against Linux community could deter its further software development activities indeed.

The series of patent infringement disputes on software patents against the Linux community motivated some Linux-based software companies and vendors to build a defensive patents pool, namely Open Invention Network (OIN) in 2005.[2] The OIN was jointly founded by Novell, Sony, NEC, IBM, Red Hat, and Philips. It amasses patents that can threaten the Linux communities for patent infringement. Then, it gives royalty-free licenses

[1] http://archive.fortune.com/magazines/fortune/fortune_archive/2007/05/28/100033867/index.htm

[2] https://www.openinventionnetwork.com/about-us/

to the patents to anyone who wants to use or develop the Linux-based program. In return, the licensees are required to permit the use of their patents by other licensees of OIN. Under the OIN program, the OIN licensees can avoid the probable patents infringement disputes with other licensees of OIN.

OSS appears to have an inherent conflict with the patent law. Patents confer patent holder the right to exclude others from using the patented invention, whereas OSS allows anyone to use, modify, and distribute the software which contains patented technology for free.

However, OSS can be compatible with patent law, at least, under GPL scheme. When OSS vendors distribute software under the GPL terms, it implies that the vendor automatically licenses the patented technology implemented in the software for free (i.e., implicit patent licensing, see Section 7 GPL v2[3]). Yet, patents implemented in OSS are not always necessarily licensed for free. If a patent holder does not distribute its software under the GPL terms, third parties cannot utilize the patent nor distribute the software that contains the patented technology if the patent holder does not formally license it. Even if the software is licensed under the GPL scheme, the patent is not automatically licensed to the third parties if the licensees do not comply with GPL terms.

3.3 Model

In this section, I explore how a firm's consolidation of existing patents and resulting patent monopoly may affect the follow-on innovation development by using an analytical model.

3.3.1 Setting

Consider that there are three firms and two patented upstream technologies, T1 and T2. Each of technologies can generate two follow-on innovations, D1 and D2 respectively with R&D investment S. In this model, I posit that D1 and D2 are horizontally differentiated

[3] https://www.gnu.org/licenses/old-licenses/gpl-2.0.en.html

products. For instance, T1 and T2 are patents on digital information searching algorithms. T1 provides a way of searching a queried information faster but less accurately than T2. In contrast, T2 is an algorithmic method to search information more accurately but slowly than T1. Web search engines that implement each of the patented algorithms become D1 and D2.

Firms 1 and 2 have stakes in developing D1 and D2 whereas firm 3 does not. Firm 3 only owns the patent on T2. Initially, firm 1 owns the patent on T1 and firm 2 receives the license on T2 from firm 3. In this setting, none of the firms consolidate the existing patents. The number of consumers who may consume D1 or D2 is given as λ.

3.3.2 Hotelling Linear City Model

In the given setting, firms 1 and 2 each creates D1 and D2. The resulting market competition can be generalized into a duopolistic market competition between the two firms with two horizontally differentiated products. Hotelling linear city model (Hotelling, 1929) is useful for formally describing this situation.

λ-consumers are evenly distributed between [0,1] while firms 1 and 2 are located at the two ends, respectively (i.e., Firm 1 at 0, Firm 2 at 1). Consumers have the homogeneous indirect utility function $U = V_0 - p_i - \tau x, i \in \{1, 2\}$, where τ is the transportation cost, x is a consumer's distance from D1, p_1 and p_2 are the market prices of D1 and D2, and V_0 is a consumer's default valuation of the follow-on innovations. The indifferent consumer between D1 and D2 is located at $x = \frac{1}{2} + \frac{p_2 - p_1}{2\tau}$.[4] Market demand for D1 (Q_1) is the number of consumers who value D1 greater than D2. Thus, $Q_1 = \lambda x = \frac{\lambda}{2} + \frac{\lambda(p_2 - p_1)}{2\tau}$. Similarly, Q_2 is derived as $Q_2 = \lambda(1 - x) = \frac{\lambda}{2} + \frac{\lambda(p_1 - p_2)}{2\tau}$. Firms 1 and 2 find the optimal prices by solving the following profit maximization problem:

$$\max_{p_i} \lambda p_i (\frac{1}{2} + \frac{p_j - p_i}{2\tau}) - S, i, j \in \{1, 2\}, i \neq j \tag{3.1}$$

4 x is the solution of the equation $V_0 - \tau x - p_1 = V_0 - (1 - x)\tau - p_2$

The maximized profit of each firm is:

$$\pi_d^* = \frac{\lambda}{2}\tau - S \tag{3.2}$$

Meanwhile, if there is only one follow-on innovation created, the firm that developed the follow-on innovation becomes a monopolist. In this case, consumers with $V_0 \geq \tau x + p_i$ will consume the follow-on innovation. Hence, the market demand for the follow-on innovation is given as $Q_i = \frac{\lambda(V_0 - p_i)}{\tau}$. The monopolist finds the price by solving the following problem:

$$\max_{p_i} \lambda p_i (\frac{V_0 - p_i}{\tau}) - S, i \in \{1, 2\} \tag{3.3}$$

The calculated maximum profit is:

$$\pi_m^* = \frac{\lambda}{4\tau} V_0^2 - S \tag{3.4}$$

No Patent Transfer

In this model, it is presumed that $\tau \geq \frac{2S}{\lambda} := \tau_0$ as this condition creates the economic incentive for firms 1 and 2 to invest in developing the follow-on innovations D1 and D2. Because firm 2 initially receives the license on T2, it pays the license fee to firm 3. At the equilibrium, the license fee is firm 2's payoff from developing D2 (i.e., $\frac{\lambda}{2}\tau - S$). Firm 1 does not license the patent on T1 to firm 2 because firm 1's payoff becomes negative if firm 2 develops D1.[5] Because firms 1 and 2 invest in D1 and D2, there are two firms in market operation, and two follow-on innovations are created.

Patent Consolidation

Consider that firm 1 buys the patent on T2 from firm 3. As a result, firm 1 becomes the sole owner of the existing patents. This situation refers to the formation of patent-monopoly by

[5] Firm 1's expected payoff of investing in D1 is $-S$ because firm 2's development of D1 makes $\tau = 0$.

patent aggregation. Accordingly, firm 2 cannot invest in D1 nor D2 without the permission of firm 1 (i.e., license).

Firm 1's Strategy: After firm 1 purchases the patent, it can choose one of the following follow-on innovation investment strategies: invest in both of D1 and D2 ($\{$ALL$\}$), invest in follow-on innovation for one upstream technology while giving the license on the other to firm 2 ($\{$OPEN$\}$), or invest in follow-on innovation of only one upstream technology while not allowing firm 2's access to the other ($\{$BLOCK$\}$).

Payoffs: For simplicity, the R&D cost for developing both D1 and D2 is assumed to be $2S$. Under this assumption, Firm 1's payoff of choosing $\{$ALL$\}$ is $\lambda\tau - 2S$.[6] The payoff of choosing $\{$OPEN$\}$ consists of a direct payoff from firm 1's follow-on innovation and the license fee paid by firm 2. The direct payoff from the follow-on innovation is given as $\frac{\lambda\tau}{2} - S$. Then, firm 1 charges the exact amount of payoff that firm 2 will earn from the follow-on innovation as the license fee, which is $\frac{\lambda\tau}{2} - S$. Hence, the payoff for firm 1 of choosing $\{$OPEN$\}$ becomes the same as $\{$ALL$\}$. The payoff of choosing $\{$BLOCK$\}$ is $\frac{\lambda}{4\tau}V_0^2 - S$ because firm 1 becomes the monopolist and there will be only one follow-on innovation created.

Strategy Selection: In strategy selection, firm 1 is assumed to take the take-it-or-leave strategy. Because $\{$ALL$\}$ and $\{$OPEN$\}$ are indifferent strategies for firm 1, firm 1 compares the payoff of these two strategies with the payoff of $\{$BLOCK$\}$.

$\{$ALL$\}$ or $\{$OPEN$\}$ (hereafter, $\{$A/O$\}$) becomes the dominant strategy when τ is such that $\lambda\tau - 2S \geq \frac{\lambda}{4\tau}V_0^2 - S$. According to the solution with the constraint $\tau \geq 0$, firm 1 chooses $\{$A/O$\}$ when $\tau \geq \frac{S+\sqrt{S^2+\lambda^2V_0^2}}{2\lambda} := \tau_1$. However, when $\tau < \tau_1$, firm 1 chooses $\{$BLOCK$\}$.

Patent Price and Incentive: Why would firm 1 buy the patent on T2? Why wouldn't firm 2 purchase the patent on T2? Does firm 3 have an incentive to sell the patent on T2?

When firm 1 chooses $\{$A/O$\}$, it can earn $\frac{\lambda\tau}{2} - S$ additionally by purchasing the patent

[6] $2 \times (\frac{\lambda\tau}{2} - S)$

on T2. Hence, the maximum price that firm 1 is willing to pay for buying the patent on T2 is $\frac{\lambda\tau}{2} - S$. Because this price is positive, firm 1 has an incentive to purchase the patent on T2. Meanwhile, firm 3 earns $\frac{\lambda\tau}{2} - S$ by selling the patent, which is the same as licensing the patent to firm 2. Hence, firm 3 is indifferent about whether to license the patent to firm 2 or sell it to firm 1.

When firm 1 chooses $\{$BLOCK$\}$(i.e., $\tau < \tau_1$), the incremental profit for firm 1 from the patent purchase is $\frac{\lambda(V_0^2 - 2\tau^2)}{4\tau}$ which is always greater than $\frac{\lambda\tau}{2} - S$. In this case, firm 3 earns a greater profit by selling the patent on T2 to firm 1 than by licensing T2 to firm 2. Hence, firm 3 has an incentive to sell the patent to firm 1, while firm 1 still has an incentive to purchase the patent on T2.[7]

Firm 2's payoff of purchasing the patent on T2 is $\frac{\lambda\tau}{2} - S$, which is the same as the payoff for receiving the license on T2. Thus, the incremental payoff from purchasing the patent on T2 is 0, which indicates that firm 2 has no incentive to switch from licensing to purchasing the patent.

Number of Follow-on Innovations: When firm 1 chooses $\{$ALL$\}$, there will be only one firm in the market operation while two follow-on innovations created. When firm 1 chooses $\{$OPEN$\}$, the number of created follow-on innovations is two, and there will be two firms in operations. Firm 1's choose of $\{$OPEN$\}$ does not affect the rate of follow-on innovation. However, if firm 1 chooses $\{$BLOCK$\}$, it invests in the follow-on innovation of one upstream technology while firm 2 can develop neither D1 nor D2. Hence, there will be only one firm in market operation, and one follow-on innovation created.

3.3.3 Comparative Analysis

Figure 3.1 shows the number of follow-on innovation before (I_{NT}) and after the creation of patent monopoly by patent transfer (I_T) according to the value of τ. The dashed line is I_{NT}. The solid line presents I_T.

7 Firm 1 can offer the price of the patent in between the $\frac{\lambda\tau}{2} - S$ and $\frac{\lambda(V_0^2 - 2\tau^2)}{4\tau}$ so that firm 1 retains a positive incremental profit while making firm 3 better off than licensing the patent to firm 2.

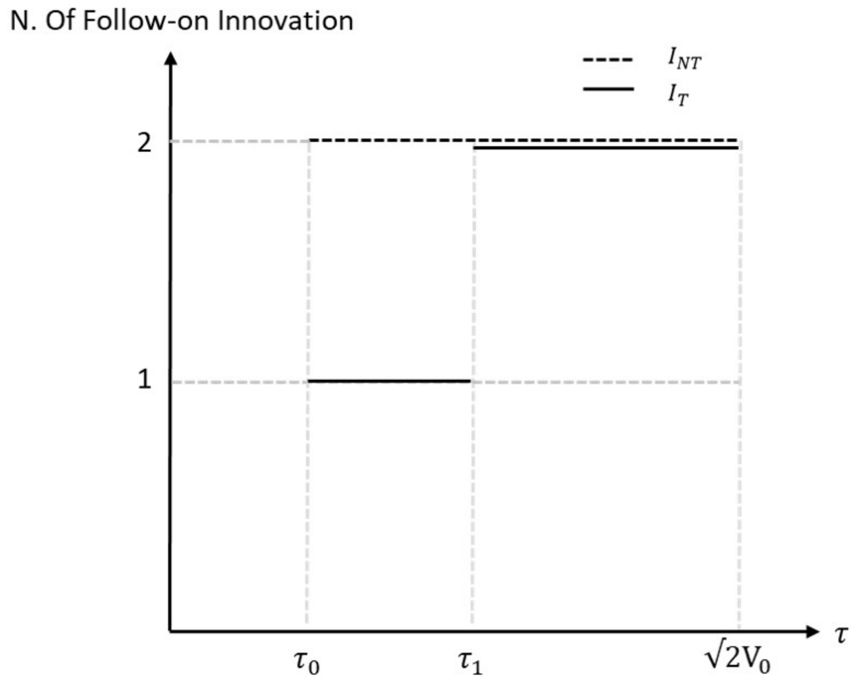


Figure 3.1: Number of Follow-on Innovations

The number of the follow-on innovation does not change when τ is sufficiently large (i.e., $\tau \geq \tau_1$). In contrast, if follow-on innovation for each upstream technology is not sufficiently differentiated from each other (i.e., $\tau_0 \leq \tau < \tau_1$), the patent consolidation results in blocking firm 2's creation of follow-on innovation while firm 1 will invest in follow-on innovation for only one upstream technology. This is so because developing marginally different follow-on innovation is not profitable to firm 1. The similar conclusion has been reached by the study on the effect of horizontal M&A on innovation (Richman et al., 2016).

The constructed model suggests that the formation of a patent monopoly by patents consolidation negatively affects the development of follow-on innovation only if the patent acquirer consolidates the patents on substituting technologies for what it already owned. The negative effect is primarily attributed to the discouraged development of follow-on innovation by firm 2 that could be in market competition with firm 1 if there was no patents consolidation. This observation formulates the following prediction:

When a firm consolidates patents on substituting technology for what it already owns, the regulation of such patents consolidation positively affects its market competitors' follow-on innovation development.

3.4 Empirical Setting

3.4.1 Novell's Software Patents Transfer

The empirical work of the present study is based on the case of the US DoJ's intervention into the Novell's software patents transfer to CPTN holdings (hereafter, CPTN) in 2011. Novell's primary business domain was the Linux-based OSS market. It was also a founder of the OIN that is the largest non-aggressive defensive patent pool for the Linux community. By joining the OIN licensing program, firms could freely use the patents that are shared through OIN. In return, the OIN licensees and member companies (Novell, Red Hat, IBM, Philips, Sony, and NEC) were required to share their patents with other OIN licensees.

In 2010, Attachmate Inc (Hereafter, Attachmate) announced that it acquires Novell Inc. Before the acquisition, Novell tried to sell about 800 software patents. Four large proprietary software companies (MS, Oracle, EMC, and Apple) established a consortium called CPTN for the acquisition of the Novell patents.[8] A two-stage patent acquisition process was planned. CPTN acquired all the Novell patents first. Then, it redistributed the patents to its member companies later. For this deal, CPTN paid $450 million in cash.

Before December 2010, it was known that Microsoft and some unknown parties made the patents transfer deal with Novell.[9] In early December 2010, the German Federal Cartel Office (*Bundeskartellamt*) fully disclosed who were behind the CPTN holdings (MS, Oracle, Apple, and EMC). After this information disclosure, there was opposition to this deal by open software advocates. The Open Software Initiative (OSI) requested the German au-

[8] see, `http://www.zdnet.com/article/microsoft-backed-cptn-alters-novell-patent-acquisition-terms-to-appease-antitrust-authorities/`

[9] `https://www.sec.gov/Archives/edgar/data/758004/000119312510265964/d8k.htm`

thority's investigation into whether the Novell's patents transfer deal violated the German antitrust law. In late December 2010[10], the OSI and the Free Software Foundation (FSF), another open software advocate, sent a letter to the US DoJ to express their concern that the Novell's patents transfer would destroy the Linux community and consequently deter its innovation. They argued that:

- Novell was dedicated to promoting the Free/Libre and Open Software (FLOSS), while using their patents primarily for defensive purpose.
- Linux software is the major competitor against products of CPTN member companies.
- CPTN member companies already have major market share in the market for operating systems, virtualization software, and middleware.[11]

The OSI and FSF were concerned that CPTN members would use Novell patents to prevent further development of OSS. They feared this because the CPTN members were not obliged to share their patents with the Linux community while they were in the software market competition with the OIN members.

The US DoJ responded to this concerns by starting an investigation into whether Novell's patent transfer violated Section 7 of the Clayton Act. According to the FSF, DoJ requested detailed information about the patents transfer deal from CPTN in late January 2011.[12] The 8-K document filed by Novell reports that there was another round of request by DoJ for further information about the deal in March 2011.[13] On April 20, 2011, DoJ announced that it intervenes in the deal to address the immediate antitrust concern. The intervention was a partial prohibition of the patents transfer.

[10] See `https://opensource.org/statements/CPTN`
[11] see, `https://www.fsf.org/news/osi-fsf-joint-position-cptn`
[12] see, `https://www.fsf.org/blogs/licensing/doj-cptn-followup`
[13] See, `https://www.sec.gov/Archives/edgar/data/758004/000119312511104372/d8k.htm`

First, MS was not allowed to acquire any of Novell patents. The patents that could be acquired by MS were to be transferred to CPTN and then transferred back to Novell (later held by Attachmate). As a result, neither MS nor the other CPTN members could acquire titles to these patents. Instead, MS was permitted to receive licenses for the patents retained by Novell and acquired by the other member companies of CPTN. Second, EMC agreed not to acquire 33 virtualization software-related patents (i.e., virtual machine (VM) technology) because EMC was the dominant player in the virtualization software market.[14] Third, all the patents retained by Novell became subject to GPLv2 and OIN licensing. Thus, even though Novell dis-joined the OIN, the patents retained by Novell kept being shared through the OIN license program.

The DoJ's partial regulation of Novell's patent transfer is a useful case to test the derived theoretical prediction. First, the CPTN members were the dominant software market players who already owned many software patents. Thus, the transfer of the Novell patents could result in consolidation of patents on substituting software technology for what CPTN members already owned. Second, the trigger of the DoJ's intervention was the German authority's disclosure of the list of CPTN members. Hence, the US DoJ regulation was close to an exogenous event to the involved parties in the patent transfer deal. Third, the DoJ's intervention was not to regulate the transfer of a specific set of patents that were particularly important for Linux software development. Instead, DoJ prohibited the transfer of patents that MS tried to acquire.

3.4.2 Data

I started by identifying the US patents that were transferred from Novell to CPTN, recorded in the USPTO patent assignment database (Graham et al., 2018). My initial search identified 866 patents. From these, I included 760 granted patents into the sample.

In the empirical analysis, I used a variable that counts the number of patents-citation

[14] According to the data, many of the VM patents (searched by virtual machine) was transferred to Oracle.

accrued to a patent in question beginning four years before to the DoJ's intervention date (i.e., April 20, 2011) as a control variable. To avoid the truncation problem in use of this variable, I excluded the patents that were filed after April 21, 2007. As a result, 432 patents retained.

For each patent in the data, I identified which company became the new patent owner by searching for the patent ownership change history made by CPTN as the patent assignor after April 2011.[15] Among 432 patents, 97 (22.5%) patents were transferred to Oracle (September 2011), 100 patents (23.2%) were reassigned to Apple (June 2012), and EMC became the new owner of 109 patents (25.2%) (September 2011). The rest of the patents (126 patents, 29.2%) were re-transferred to Novell (September 2011). Because DoJ ruled that the patents that could be transferred to MS must be retained by Novell, the 126 patents are the transfer-prohibited patents (hereafter, regulated patents). Figure 3.2 depicts the redistribution of Novell's patents.

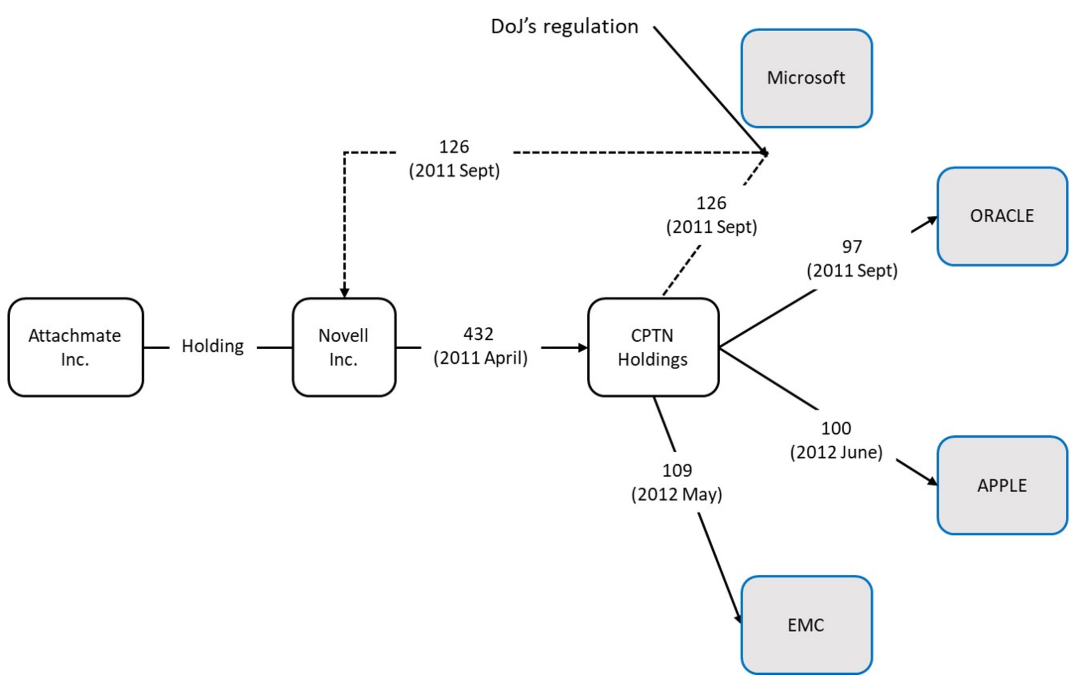


Figure 3.2: Transfer of Novell Patents

I obtained detailed information of each of the patents from patentview.org (serviced by

[15] Identified by execution date.

USPTO). The distribution of NBER subcategories shows that most of the 432 patents were related to software indeed (181 Computer Hardware & Software, 103 Electronic Business Method & Software, and 99 information storage).

3.4.3 Variables

Dependent Variables

I define a follow-on innovation as a new technical idea that was built upon a previously existing inventive idea. Based on this definition, I operationalized the number of follow-on innovation of a patent by using the patent forward citation that a patent received in a certain time window (e.g., Galasso and Schankerman, 2014; Gaessler et al., 2017; Drivas et al., 2017). Note that this empirical strategy has several limitations. Not all patented inventions are commercialized and, hence, subsequent patent of a focal patent invention may not be the valid proxy for "innovation." Also, some innovation may not be the subject of patenting in the first place. The innovators used not to patent their innovation for various reasons, or the innovative idea is not the patentable subject matter by law. However, it is not deniable that the patent citation is one of the most reliable and available sources to measure technological linkage between the inventive ideas contained in the citing and cited patents and captures the cumulative nature of inventions in the citing patents (e.g., Jaffe and Trajtenberg, 2002; Kang and Motohashi, 2014; Jaffe and de Rassenfosse, 2017). This is because the patent citation is made when the novelty and legal scope of the invention in question is limited by the cited patents (i.e., prior arts). In addition, due to the fact that only inventions which are "useful" and "novel" are patentable, the issued patent can be considered as the legally curated inventive idea that may bring in innovation.

I employ four patent forward citation variables counting from the beginning on the date of DoJ's intervention and up until four years later. The first two variables are to test the derived theoretical predictions, and the last two variables are used to examine the impact of the regulation in a more comprehensive manner.

The first dependent variable, **PostCiteOIN**, accounts for the number of forward citations originated from the patents belonging to the members of OIN excluding Novell (i.e., Sony, NEC, IBM, Red Hat, and Philips). This variable proxies for the number of follow-on inventions created by the OIN members that competed with the CPTN members in the software market. The second dependent variable is **PostCiteCPTN** that accounts for the number of forward citations made by the CPTN members' patents. This variable proxies for the number of follow-on inventions created by the firms that were trying to consolidate the Novell patents. The third variable, **PostCiteRem**, accounts for the number of forward citations from the patents that were owned by those who were not the OIN nor CPTN members. Finally, to examine how the DoJ's intervention affected the overall rate of all the follow-on inventions, I regress **PostCiteAll** that accounts for the total number of forward citations that a patent in question received.

Independent Variable

The independent variable is a binary variable labeled to **regulated**, which takes the value of 1 for the regulated patents and 0 for the transferred patents, by considering the DoJ's intervention as a policy treatment. The regulated patents comprise the treatment group and the transferred patents belong to the control group. One may argue that the regulated patents should belong to the control group because the DoJ's regulation sustains status-quo of the patents ownership. However, due to the regulation in the context of this study is an authority's intervention into the free market transaction of patents, it is more reasonable to consider it as a manipulative factor (e.g., Choi and Philippatos, 1983; Crandall and Winston, 2003).

Control Variables

First, I control for the number of created follow-on inventions of each patent based on the number of its forward-citations that the patent of interest received from beginning four years before the date of DoJ's intervention. Because the full list of the CPTN member companies was disclosed in December 2010, I count the number of forward citations up to six months before the regulation date. By introducing this variable, I control for the pre-regulation difference in the number of follow-on inventions between regulated- and transferred-patents. **PreCiteOIN**, **PreCiteCPTN**, **PreCiteRem**, and **PreCiteAll** are the pre-treatment control variables for each of the dependent variables.

Second, I control for the patent's legal scope using the number of independent patent claims (**nClaim**). The broader its legal scope, the greater the probability that the patent limits the legal scope of subsequent patents (Marco et al., 2016) and the greater the probability of the patent being involved in patent infringement litigation (Lanjouw and Schankerman, 1997). Because patents with a broad legal scope could be useful in strategic patent enforcement, MS might be interested in acquiring these, while their transfer could particularly catch the attention of DoJ.

Third, as DoJ stated, its primary concern was the probable discouragement of further development of Linux-oriented applications, middleware, virtualization software, and operating system as a result of the patent transfer deal. Thus, the transfer of patents relevant to these application areas could have become the primary target of the DoJ's intervention, since MS targeted these patents for strategic purpose. Meanwhile, because these applications could be related to the emerging technological opportunity in the software market, the relevant patents could have received more patent citations than patents for other applications. To rule out this spurious effect, I introduce a binary variable **DoJConcern** that takes the value of 1 if the patent of interest contains at least one of the following keywords in its abstract[16]: linux, unix, software, middleware, open source, operating system, and virtual machine. The search identified 98 patents in the sample.

Fourth, the member companies of OIN had major stakes in the GNU/Linux software market while the GNU/Linux software was the primary competitor of MS products. Hence,

[16] I used the curated abstracts provided by Derwent Innovation Index of Clarivate Analytics.

MS might had the incentive for preempting patents that closely relate to OIN members' technologies for the monopolistic market profit (See the "incentive for a firm to preempt patents for monopolistic market profit", Chang, 1995). At the same time, patents relevant to the technological domain of the OIN members could have been within a promising technology area, and thus attract more follow-on inventions than other software patents do. To rule out this hypothesis, I control for whether the patent of interest has technological link with the patents owned by the OIN members by using the patent citation information. **CiteOINPat** takes the value of 1 if the patent of interest cites patents owned by the OIN members before the DoJ intervention, and 0 otherwise.

Fifth, the genuine value of a patent is realized as a patent portfolio (Parchomovsky and Wagner, 2005; Choi and Gerlach, 2017). Firms used to obtain patents to strengthen their patent portfolio by organizing it as a well-interconnected web of intellectual property rights. In this regard, MS probably tried to acquire Novell patents that are related to the patents that MS already owned. Meanwhile, the patents closely related to MS' patents might be relevant to a rising technological opportunity in the software market, which attracts more follow-on inventions than others. To control for this effect, I introduce **CiteMSPat** as a control variable which takes the value of 1 if the patent of interest has cited any MS-owned US patents before the DoJ's intervention.

Sixth, the Novell's patents transfer was the subject of the German authority' investigation regarding the violation of the German antitrust law. Hence, those patented inventions that were protected in Germany could have caught the attention of the German authority, which triggered the intervention of US DoJ in the end. As many studies show, patents with protections in multiple jurisdictions often contain commercially valuable inventions (e.g., Lanjouw et al., 1998; Harhoff et al., 2003). It is also plausible that MS had planned to purchase Novell's commercially valuable patents in the first place. I control for this effect by introducing **EuroFam** that takes the value of 1 for the Novell patents having EPO family patents. Finally, I control for the patent application year (**AppYr**) and technology (**Tech**) field fixed effects by using NBER subcategory (Hall et al., 2001).

3.4.4 Descriptive Analysis

Table 3.1 provides the summary statistics for the variables of interest. A simple comparison of the mean values reveals notable differences between the regulated and transferred patents in all the four forward citation indicators. On average, the regulated patents received more citations both before and after the DoJ's intervention than the transferred patents. This indicates that, even though the DoJ's intervention was triggered by a seemingly exogenous event, the two groups of patents are different in their technological importance.

Table 3.1: Summary Statistics

	Regulated (N=126)		Transferred (N=306)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
ln(PostCiteOIN+1)	0.37	0.64	0.22	0.47
ln(lPostCiteCPTN+1)	0.55	0.84	0.43	0.68
ln(PostCiteRem+1)	1.73	1.25	1.36	1.18
ln(PosteCiteAll+1)	2.01	1.26	1.63	1.15
ln(PreCiteOIN+1)	0.55	0.69	0.40	0.59
ln(PreCiteCPTN+1)	0.57	0.79	0.48	0.68
ln(PreCiteRem+1)	1.67	1.16	1.29	1.12
ln(PreCiteAll+1)	1.96	1.19	1.58	1.15
nClaim	23.04	12.09	22.39	11.23
DoJConcern	0.20	0.40	0.24	0.43
CiteOINPat	0.78	0.42	0.77	0.42
CiteMSPat	0.38	0.49	0.43	0.50
EuroFam	0.07	0.26	0.22	0.42
AppYr	1999.71	3.82	2000.57	3.97

Table 3.2 presents the correlations between the key variables. Except for the correlations between the forward citation-based variables, the correlations are below 0.3.

Table 3.2: Correlation

Variables	ln(PreCiteOIN+1)	ln(PreCiteCPTN+1)	ln(PreCiteRem+1)	ln(PreCiteAll+1)	Regulated
ln(PreCiteOIN+1)	1.00				
ln(PreCiteCPTN+1)	0.34	1.00			
ln(PreCiteRem+1)	0.41	0.35	1.00		
ln(PreCiteALL+1)	0.57	0.56	0.94	1.00	
Regulated	0.11	0.06	0.15	0.15	1.00
nClaim	0.15	0.12	0.24	0.24	0.03
DoJConcern	0.07	0.01	0.02	0.03	-0.04
CiteOINPat	0.02	-0.01	-0.02	0.01	0.01
CiteMSPat	-0.02	0.01	-0.09	-0.07	-0.04
EuroFam	-0.07	-0.04	-0.08	-0.11	-0.18

Variables	nClaim	DoJConcern	CiteOINPat	CiteMSPat	EuroFam
ln(PreCiteOIN+1)					
ln(PreCiteCPTN+1)					
ln(PreCiteRem+1)					
ln(PreCiteALL+1)					
Regulated					
nClaim	1.00				
DoJConcern	0.02	1.00			
CiteOINPat	0.06	0.00	1.00		
CiteMSPat	-0.06	0.09	0.16	1.00	
EuroFam	0.00	-0.08	-0.01	-0.07	1.00

3.5 Results

3.5.1 Regression Results

I employ the econometric model that was employed by the study of Galasso and Schankerman (2014). Because this model controls for the pre-intervention dependent variable, the specification is cross-sectional DiD model. The Ordinary Least Square (OLS) estimator with robust standard error is used. For the estimation, I take natural logarithms on the four forward-citation variables added by 1 because these variables have right-skewed distributions and zero as the minimum value. The econometric model specification is as follow.

$$
\begin{aligned}
\ln(PostCiteVar_i + 1) = \beta_0 &+ \beta_1 \times regulated_i + \beta_2 \times \ln(PreCiteVar_i + 1) \\
&+ \beta_3 \times nClaim_i + \beta_4 \times DoJConcern_i + \beta_5 \times CiteOINPat_i \\
&+ \beta_6 \times CiteMSPat_i + \beta_7 \times EuroFam_i + \beta_8 \times AppYr_i \\
&+ \beta_9 \times Tech_i + \epsilon_i
\end{aligned} \tag{3.5}
$$

where $PostCiteVar_i \in \{PostCiteOIN_i, PostCiteCPTN_i, PostCiteRem_i, PostCiteAll_i\}$.

My theoretical prediction anticipates a positive and statistically significant β_1 for the $ln(PostCiteOIN_i + 1)$ while that for $ln(PostCiteCPTN_i + 1)$ is not far from 0. Table 3.3 presents the result.

The first column reports the regression result employing **ln(PostCiteOIN+1)** as the dependent variable. The regression result shows that the coefficient of regulated is positive and statistically significant at the 0.05 significance level. The rate of follow-on invention for a regulated patent becomes about 15.6% greater than that for a comparable transferred patent, after the regulation.

The second column presents the estimation result using **ln(PostCiteCPTN+1)** as the dependent variable. The coefficient of the regulated is statistically insignificant at the 0.1 significance level. This indicates that there is no evidence showing the notable difference between regulated and transferred patents in the rate of CPTN member's follow-on inventions after DoJ's intervention.

The third column presents the estimation result using **ln(PostCiteRem+1)** as the dependent variable. The coefficient of the **regulated** is statistically insignificant at the 0.1 significance level. There is no evidence showing that the DoJ's regulation influenced the rate of follow-on inventions of individuals or organizations that were not involved in the patent transfer deal.

Table 3.3: Main Regression Result

	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteRem+1)	ln(PostCiteAll+1)
Regulated	**0.156****	0.0102	0.0664	0.0679
	(0.0620)	(0.0683)	(0.0911)	(0.0886)
ln(PreCiteOIN+1)	0.339***			
	(0.0545)			
ln(PreCiteCPTN+1)		0.617***		
		(0.0581)		
ln(PreCiteRem+1)			0.902***	
			(0.0387)	
ln(PreCiteAll+1)				0.910***
				(0.0380)
nClaim	-0.00115	0.00280	0.00377	0.00312
	(0.00190)	(0.00293)	(0.00310)	(0.00301)
DoJConcern	0.0191	-0.126**	0.0381	-0.0447
	(0.0576)	(0.0624)	(0.0887)	(0.0848)
CiteOINPat	0.0956*	0.00828	0.0167	0.0326
	(0.0543)	(0.0684)	(0.0918)	(0.0898)
CiteMSPat	-0.0291	0.0203	0.0162	-0.0196
	(0.0531)	(0.0588)	(0.0761)	(0.0734)
EuroFam	-0.0297	-0.0300	-0.0641	-0.0871
	(0.0692)	(0.0708)	(0.108)	(0.104)
Constant	-0.324*	-0.498**	0.230	0.000753
	(0.183)	(0.253)	(0.238)	(0.277)
R^2	0.203	0.420	0.657	0.663
Adjusted R^2	0.142	0.375	0.630	0.637
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes
Observations	432	432	432	432

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The last column reports the estimation result using **ln(PostCiteAll+1)** as the dependent variable. Although the sign of the coefficient of regulated is positive and size is not marginal, it is statistically insignificant at the 0.1 significance level, which indicates that there is no statistical evidence for rejecting that the transferred and regulated patents are indifferent in the overall rate of follow-on inventions in the post-regulation period.

All in all, the DoJ's regulation seems to positively associate with the rate of follow-on inventions by OIN members that were in market competition with the CPTN members. Yet, there is no statistical evidence showing that the CPTN members' (the patent acquirers) rate of the follow-on inventions was impacted by the DoJ's regulation. These findings are consistent with the theoretical prediction and robust to the count-variable regression models (Negative binomial and Poisson models), a placebo test for the specificity of the finding to the timing of regulation, and sub-sample regressions. Appendix A reports the details of the robustness tests.

3.5.2 Limitations of DiD

Two assumptions must be satisfied to identify the treatment effect of interest when to employ DiD. The first assumption is that the time trend of outcome variable in the pre-treatment period between the treatment and control groups should be parallel; this is the pre-treatment time trend parallel assumption. Another assumption is that the time trend of the treatment-free outcome variable in the post-treatment period for the treatment and control groups should parallel.

The first assumption seems to be partly violated according to the empirical data (See Figure 3.3).[17] The second assumption is not testable as the counter-factual of regulated patents is unobservable.

The violations of these two assumptions make the DiD estimator biased, and thus, the regression result may not present the causal impact of the DoJ's regulation.

To mitigate these concerns, I employ the Synthetic Control (SC) approach as a complementary empirical method to the DiD analysis. The SC mechanically forces the pre-treatment period outcome of the treatment and control group to become comparable. If the outcome of the treatment and control groups can be predicted by a linear combination of selected covariates and pre-treatment outcomes, the SC yields an unbiased estimation of the treatment effect (Kreif et al., 2016). Note that even though the SC has some benefits over DiD, it also has limitations. The synthesized counterfactual is not real, and there is a possibility that the outcome variable is not sufficiently predictable by a linear combination of selected covariates and the pre-treatment outcome. However, the SC method and DiD approach may jointly identify the treatment effect better than DiD analysis alone if

[17] Although I have controlled for the difference in the pre-intervention period forward citation measures between the two groups of patents in the DiD regression, this empirical strategy is not sufficient to guarantee the pre-treatment parallel time trend of the outcome variables.

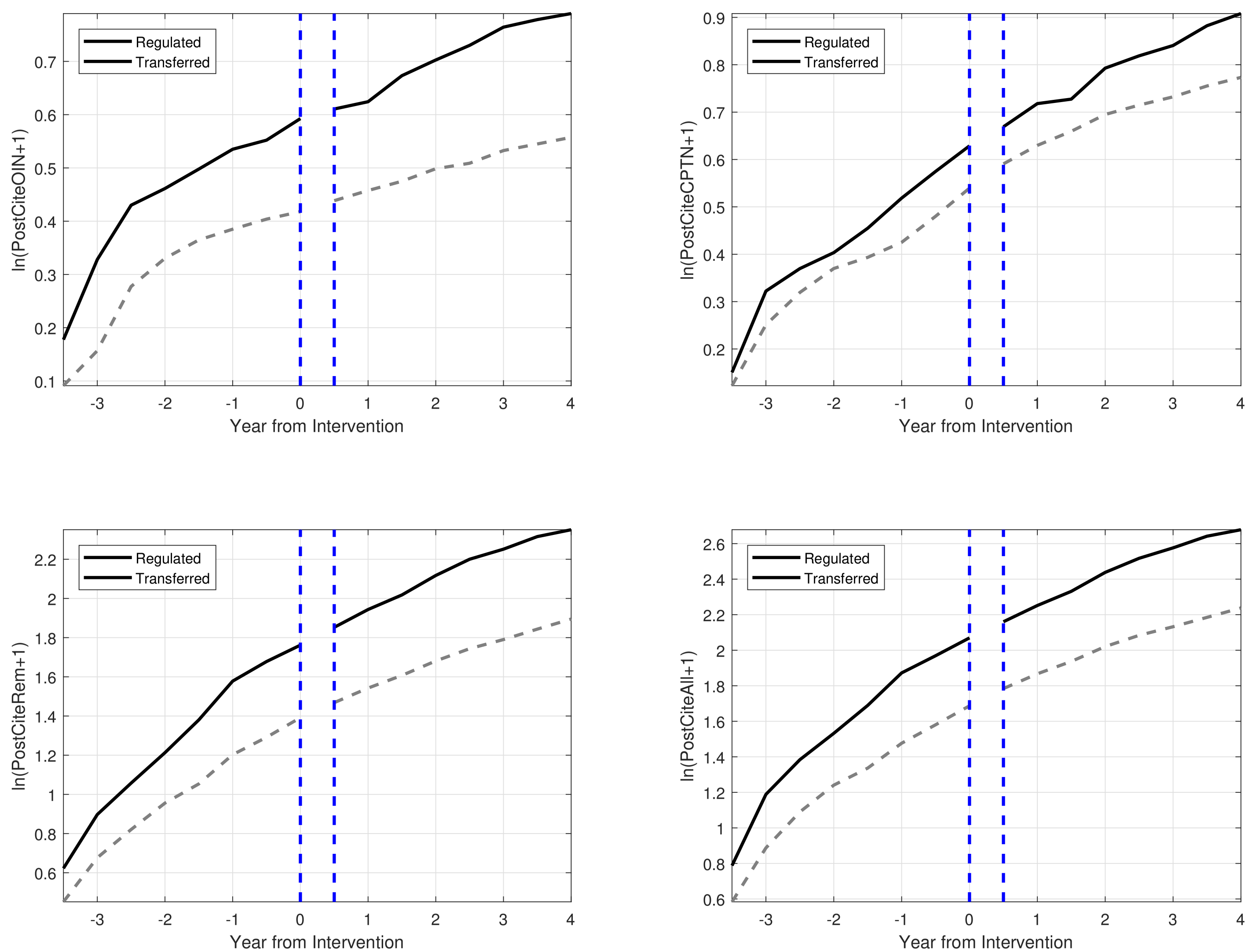


Figure 3.3: Time Trend of the Four Forward Citation Measures

these two methods yield consistent findings as the synthetic control approach can be used to validate the finding from DiD analysis (Kreif et al., 2016).

3.5.3 Synthetic Control Analysis

The dataset employed in the present study has a multiple number of regulated patents (treatment units) and transferred patents (control units). Hence, I employ the method for multiple-treated and control units case as proposed by Kreif et al.(2016). See Appendix B for the methodological details of the synthetic control approach.

I began with choosing all the control variables that were used for the DiD analysis. Then, I created the **aggregated regulated** patent by taking the arithmetic average of the selected covariates of the 126 regulated patents. Third, I constructed the synthetic control of the aggregated regulated patent. To this end, I customized the MATLAB script which was provided by Jens Hainmueller at Stanford University.[18] Table 3.4 compares the mean values of the key variables of regulated patents with those of the synthetic control.

Table 3.4: Means of Key Variables for Regulated, Synthetic-Regulated, and Transferred Patents

Variables	Regulated	Synthetic-Regulated	Transferred
Mean of PreCiteOIN	0.99	0.96	0.64
Mean of PreCiteCPTN	1.13	1.17	0.88
Mean of PreCiteRemained	5.97	6.03	4.21
Mean of PreCiteAll	8.10	8.15	5.74
PreCiteOIN	1.30	1.30	0.89
PreCiteCPTN	1.66	1.66	1.25
PreCiteRemained	9.30	9.30	6.38
PreCiteAll	12.26	12.26	8.52
nClaim	23.04	23.04	22.39
Application Year	1999.71	1999.71	2000.57
EuroFam	0.07	0.07	0.22
DoJConcern	0.20	0.20	0.24
CiteMSPat	0.38	0.38	0.43
CiteOINPat	0.78	0.78	0.77

[18] Downloaded from `https://web.stanford.edu/~jhain/synthpage.html` in August 2018.

The mean values of most of the key variables of the synthetic control are comparable to those of the regulated patents, which demonstrates that the average characteristics of constructed synthetic control are sufficiently close to those of the regulated patents.

For statistical inference, I conducted the placebo test as Abadie et al.(2010) and Kreif et al.(2016) employed. First, 126 patents were randomly selected from the transferred patents (donor pool). Then, I constructed the placebo-regulated patent by taking the average of the key variables of interest from the 126 selected patents. Second, by using the remaining patents in the donor pool (180 patents), I constructed the synthetic control for the placebo-regulated patent. This procedure is repeated 1000-times. Finally, I profiled the distribution of the difference between the accumulated forward citations measured at T=4 and T=-1, accrued by the regulated patents and 1,000 placebo-regulated patents, G. Using this distribution, I calculated the likelihood of obtaining G above the absolute value of G for the aggregated-regulated patents by chance. This likelihood becomes the empirical p-value.

Figure 3.4 shows the number of patents forward-citations accrued to a patent by OIN member companies, according to the SC-analysis. After the DoJ's intervention, the forward citations received by regulated patents from OIN member companies becomes greater than for the synthetic control. The obtained G for regulated patents is at the right tail of the distribution (empirical p-value=0.02). This result confirms that the DoJ's regulation positively affected the follow-on inventions development of OIN members.

Figure 3.5 presents the number of forward citations patents received from CPTN members. There is virtually no difference in the number of forward citations accumulated by the regulated patents and synthetic control after DoJ's intervention. The empirical p-value is 0.12, which does not reject the null hypothesis at the 0.1 significance level.

Figure 3.6 shows that there is no notable difference in the number of forward citations made by those who were not the members of CPTN nor OIN, accrued to the regulated patents and the synthetic control after the DoJ intervention. The empirical p-value is 0.243,

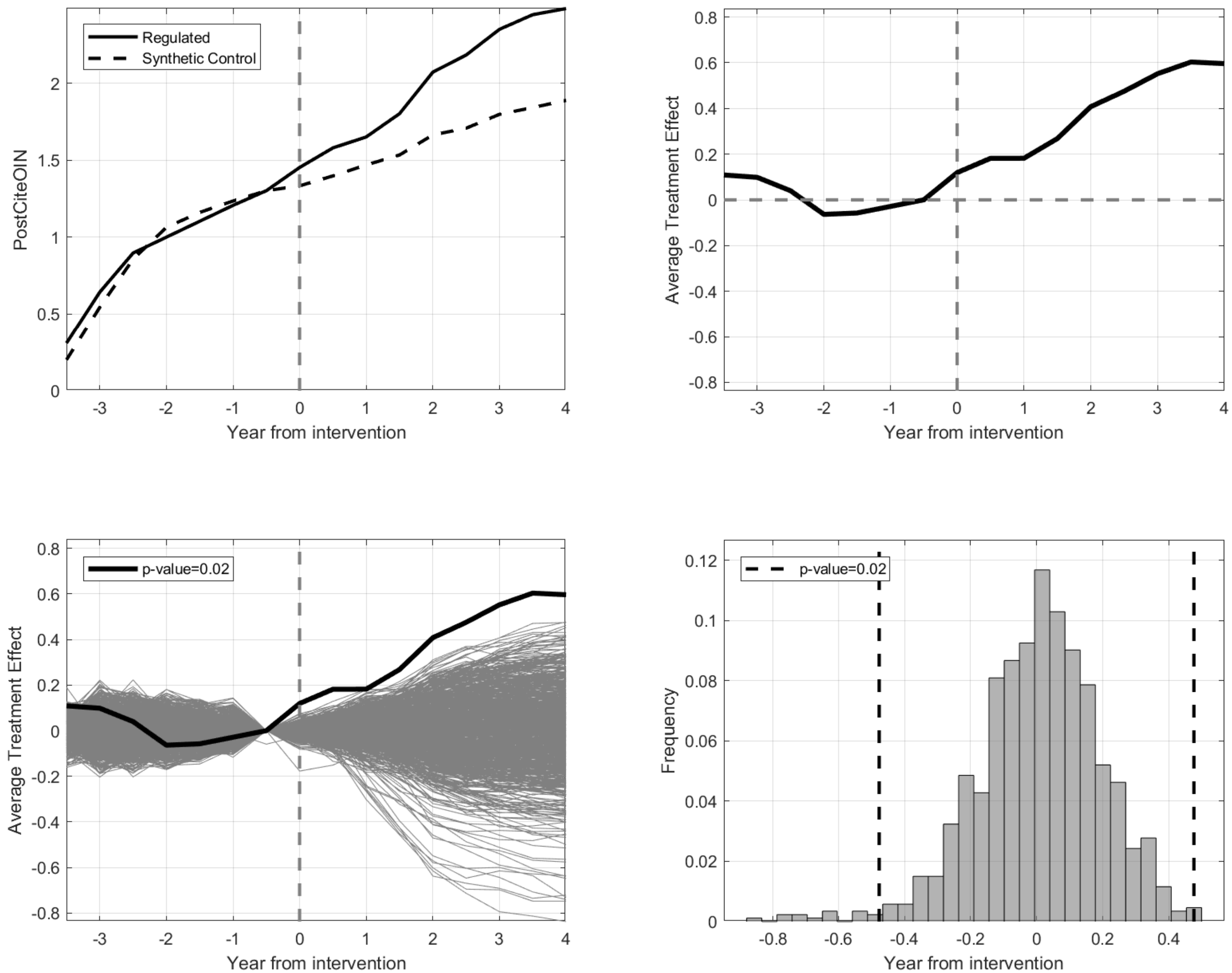


Figure 3.4: Synthetic Control Method-Forward Citation made by OIN members

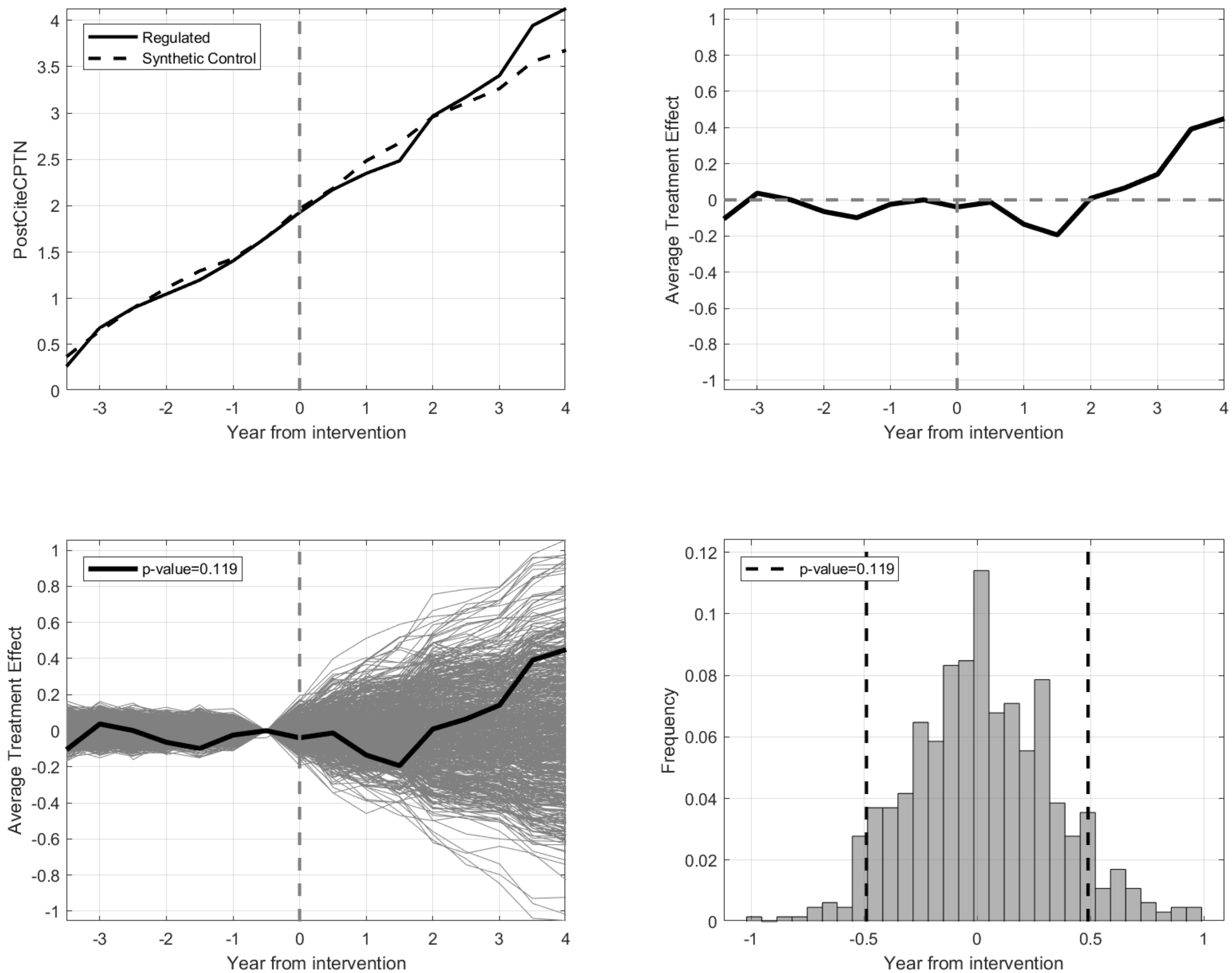


Figure 3.5: Synthetic Control Method-Forward Citation made by CPTN members

which does not reject the null hypothesis at the 0.1 significance level.

Figure 3.7 compares the total number of forward citations accrued to the regulated patents and the synthetic control. The obtained empirical p-value is 0.999, which indicates that there is virtually no difference between the two groups.

All in all, my DiD and the SC analysis conform that the DoJ's regulation positively affected the OIN members' development of follow-on inventions for the Novell's patents. I use the DiD as the primary tool for further analysis as I confirmed that the DiD and the SC method produced consistent findings.

3.5.4 Promotion or Mitigation?

My theoretical model explains that the difference between regulated and transferred patents in the post-regulation rate of OIN members' follow-on inventions is due to their decreased rate of follow-on inventions for the transferred patents—DoJ's regulation was effective to mitigate this effect (Mitigation effect). However, it is not the only one that can explain my empirical finding. The DoJ's regulation could "promote" follow-on inventions by the OIN's members without negative impact of the patent transfer (Promotion effect). The implication of one is substantially different from another, and yet, my empirical research design does not allow to distinguish these two scenarios. I address this empirical challenge by conducting an additional test.

If the mitigation effect worked, the rate of OIN members' follow-on inventions for the transferred patents should have been lower than that of comparable patents which were not involved in the transfer deal (hereafter, the counterpart patents). In contrast, if the promotion effect worked, the rate of follow-on inventions for the regulated patents created by OIN members should have been greater than that of the comparable counterpart patents. These two scenarios are not mutually exclusive. If the two scenarios worked together, the two aforementioned statements should be jointly supported.

For the test, I consider the patents that were originally filed by the four CPTN members

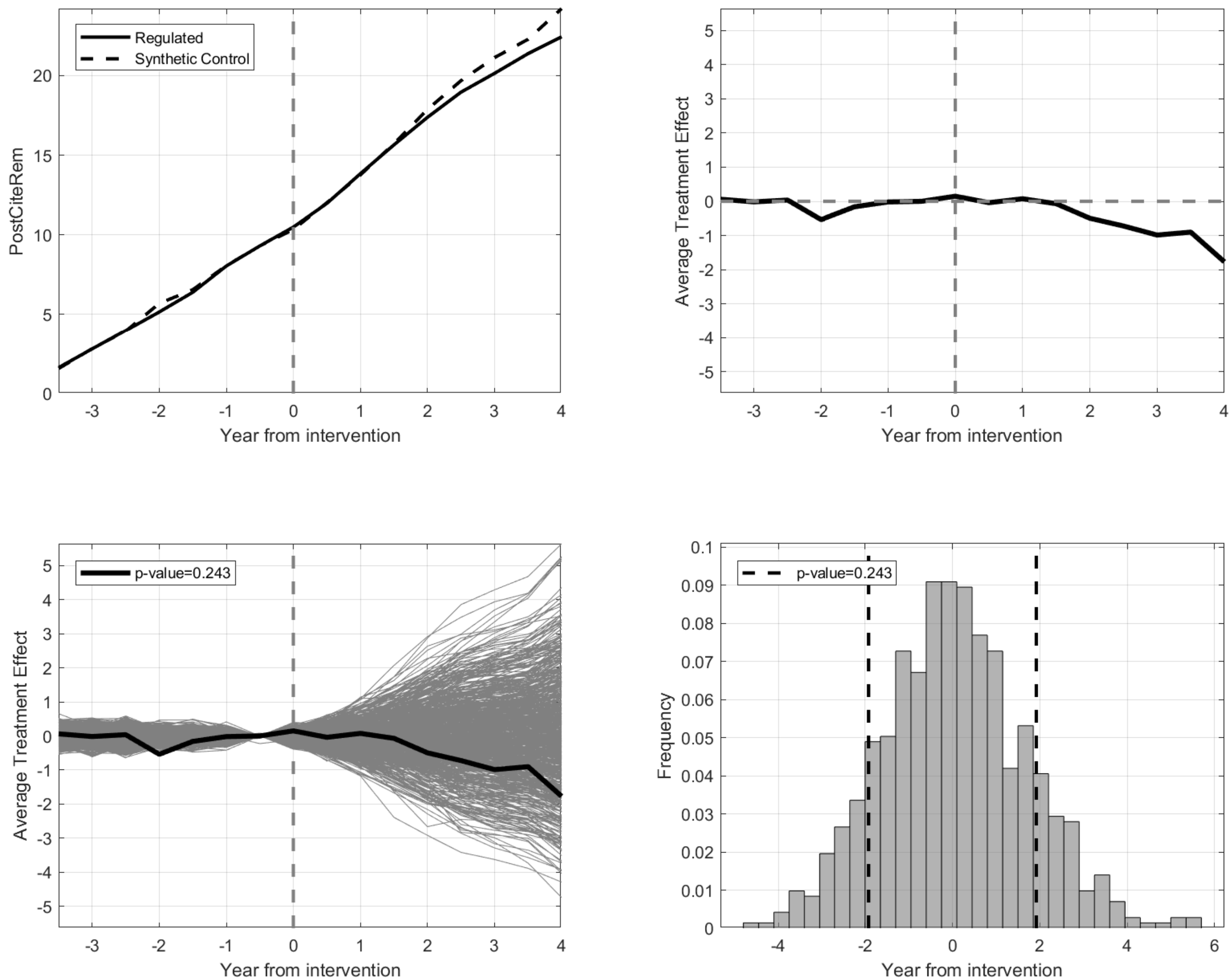


Figure 3.6: Synthetic Control Method-Forward Citation made by non-CPTN & Non-OIN members

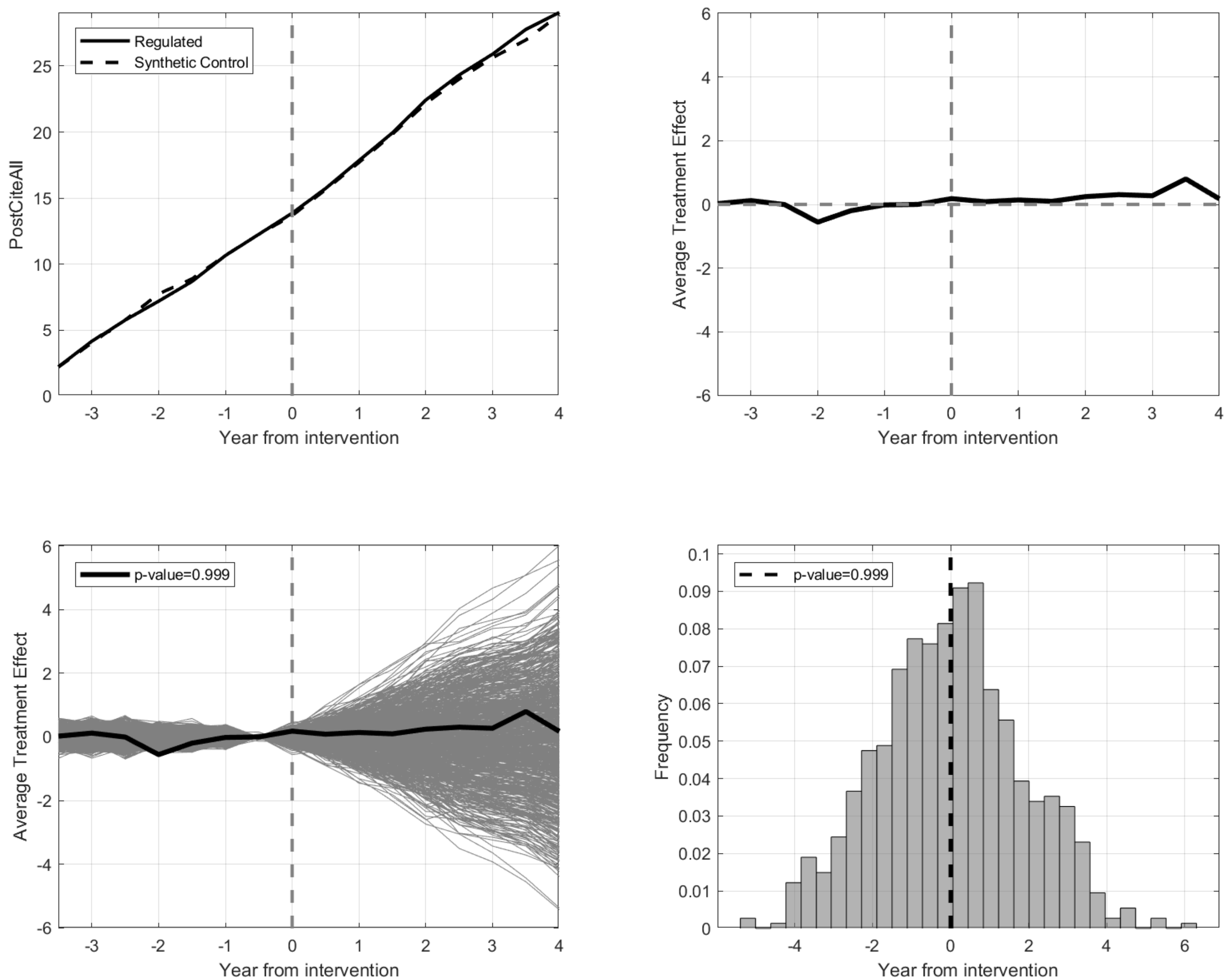


Figure 3.7: Synthetic Control Method-Total Forward Citation

as the counterpart patents. Because the CPTN members were in fierce market competition in software market with the OIN members, while all the CPTN members had great stakes in acquiring Novell patents, the patents filed by them would be sufficiently close to the Novell patents in technology space. Thus, the forward citation rate for these patents can be a reasonable baseline for this test. I chose the US patents that were originally filed by the four CPTN members between January 1, 1990, and April 20, 2007.

The regression results presented in Table 3.5 show that the rate of OIN members' follow-on inventions for the transferred patents become about 6.4% lower than that of the comparable counterpart patents in the post DoJ's regulation period. Meanwhile, the coefficients of **regulated** are positive but statistically insignificant at the 0.1 significance level. This implies that the CPTN members' consolidation of the Novell patents imposed a negative impact on the development of OIN members' follow-on inventions and thus, the DoJ's intervention mitigated this effect. Yet, there is no evidence for the existence of "promotion effect" by the regulation.

A finer way of building the counterpart patents is to find individual patents that have close "technical similarity" to the Novell patents. To this end, I benefit from the outcomes of the two recent studies by Younge and Kuhn (2016) and Kuhn et al. (2017). By analyzing the full text of the US grant patents, they calculated the pair-wise textual similarity of all the US patents and their cited patents. The textual similarity takes the value between 0 and 1 (1 for the completely same patents documents). Using the data available in their website[19], I search for patents that cite each of the Novell patents with maximum textual similarity with the cited patent. From the identified technically similar citing patent, I identify other patents cited by the selected citing patent with the maximum textual similarity, excluding the patents that were filed by Novell, OIN members, or CPTN members. Novell patents that could not find the matched patents in this algorithm were dropped from the sample. This matching procedure remained 370 Novell's patents and found 370 matched counterparts

[19] https://www.patrf.org/research/

patents (replacement allowed). If the regulation mitigated the negative impact of the patents transfer on the OIN member's follow-on inventions, the OIN member's rate of follow-on inventions for the transferred patents should have been lower than that of the textual-similarity matched patents. In contrast, the post-regulation OIN's follow-on inventions for the regulated patents should be indifferent from that of the matched patents. Table 3.6 presents the test result.

The result shows that the rate of the OIN members' follow-on inventions for the transferred patents is still far less than that for textual-similarity based matched patents. Indeed, the coefficients of **transferred** in the first and third columns takes negative values and they are statistically significant at the 0.01 significance level. In contrast, there is no evidence showing a significant difference between the regulated patents and the matched patents in the rate of OIN members' follow-on inventions. Regression results presented from the fourth to sixth columns indicate that there is no evidence showing the difference in the CPTN members' rate follow-on inventions for the Novell patents. This additional analysis confirms that the direction of the impact of the regulation was of "mitigating" the negative impact of the CPTN's patents consolidation for the OIN member's development of follow-on inventions, as predicted by the theoretical model.

3.5.5 Buyer's Effect vs. Regulation Effect?

The true counter-factual in the present study's context is "what if Microsoft could acquire the regulated patents." In the main analysis, I used the Novell patents that were transferred to Oracle, EMC, and Apple as a comparison group. A downside of this empirical strategy is that it cannot isolate the effect of the antitrust regulation from the probable effect by the fact that the patents acquirer was not MS. The effect of regulation could be particular for the patents consolidation by the three firms of the CPTN, not necessary so if MS was the patents acquirer. If my finding originated from such buyer's effect, the finding might not present the causal impact of the regulation.

To address this concern, I replace the comparison group with the software patents that were purchased by MS from America Online Inc. (AOL) in June 2012. In 2012, AOL announced that it sells some of its software patents to MS for patents monetization.[20] AOL also involved in developing open-source software as Novell did and its patent sales timing was close enough to the Novell's patents transfer (i.e., 1-year difference). Hence, AOL's patents that were sold to MS (hereafter, AOL-MS patents) can be a reasonable alternative comparison group of the regulated patents. If my finding was not driven by the buyer's effect, the similar finding as that of the main regression result likely to be observed. In contrast, if the patent buyer effect was the prevailing driver of my finding, the rate of follow-on inventions for the regulated patents and the AOL-MS patents should be indifferent.

I collect information on the US patents that were transferred from AOL to MS in June 2012[21], which were filed before June 2008 (4-year before the transfer), from the USPTO patent assignment data. My search identifies 90 patents. Then, I conduct the regression analysis using the two dependent variables ($ln(PostCiteOIN+1)$, $ln(PostCiteCPTN+1)$). Table 3.7 presents the regression result.

The statistical significance of the coefficients of **regulated** is largely consistent with those in the main regression result. Meanwhile, the coefficient of **transferred** is statistically insignificant at the 0.1 significance level. This result indicates that my finding was driven by which CPTN's patents consolidation negatively affected the OIN members' development of the follow-on inventions, rather than the "buyer's effect."

3.5.6 Did DoJ Prevent Technology Transfer?

Patents transfer can serve an alternative way of transferring technology (Jeong et al., 2013). If MS intended to acquire underlying "technology" of the Novell's patents, MS' acquisition

20 see https://techcrunch.com/2012/04/09/aol-sells-800-patents-for-1-billion-to-microsoft-memo-to-staff/;https://www.businesswire.com/news/home/20120409005434/en/AOL-Microsoft-Announce-1.056-Billion-Patent-Deal

21 Identified by execution date

of the Novell patents could encourage its future development of follow-on inventions. In this case, DoJ's regulation could be of regulating technology transfer from Novell to MS. I test the credibility of this argument by capitalizing on the MS' selection of Novell patents for the acquisition and the fact that DoJ allowed MS to receive licenses of all of the Novell patents in the end.

MS and other CPTN members selected a set of patents that they will acquire from Novell. Attachmate (the acquirer of Novell) retained the leftover patents and collateralized them to Suisse Credit for financing in April, 2011.[22] This indicates that MS had two sets of Novell patents in choosing patents for acquisition in the begining: patents that MS originally wanted to acquire (later, these patents become regulated patents), and patents that were not chosen by MS for acquisition (later, transferred patents and leftover patents). Because MS was allowed to receive licenses of all of the Novell patents afterall, it was able to access the Novell technology eventually. If MS intended to acquire the "Novell's technology" by purchasing the patents, then, MS should have developed more follow-on inventions for the regulated patents than the patents that it did not choose to acquire. That is, the rate of MS' follow-on inventions for the regulated patents should be greater than that of the transferred and the leftover patents.

For the empirical test, I additionally collected the information about the leftover patents by identifying the patents that were collateralized through Suisse Credit in April 2011. From these patents, I excluded the patents that were filed after April 20, 2007, for the use of four-year window forward citation variable as a control variable. Finally, I obtained the 124 "leftover patents."

The dependent variable is the **ln(PostCiteMS+1)** that accounts for the number of forward citations made by MS in the post-regulation period. The independent variable is the **regulated**.

[22] Credit Suisse was one of the financial advisers of Attachmate, and Novell collateralized the leftover patents to the Credit Suisse in April 2011, `https://www.reuters.com/article/us-novell/novell-sells-itself-in-two-part-2-2-billion-deal-idUSTRE6AL2WD20101122`

Table 3.8 reports the test result. The first column reports the regression result comparing the MS' forward citation for regulated and transferred patents. The coefficient of **regulated** remains statistically insignificant at the 0.1 significance level. The second column presents the regression result comparing the MS' forward citation for regulated and leftover patents. The coefficient of **regulated** is statistically insignificant at the 0.1 significance level. This result indicates that there is no evidence supporting that the MS intended to acquire the Novell's technology.

3.5.7 Patent or Invention? Evidence from Copyright and Trademark Data

In my research design, I used patents as the outcome of the inventive activities of the patentee. Accordingly, my finding may merely indicate decreased software "patenting" activities of OIN members by the partial transfer of Novell patents to the three CPTN members, rather than their overall software innovation activities. This alternative explanation is of particular interest in that the partial transfer of Novell patents could impact the direction of OIN members software innovation. To address this concern, I conduct a descriptive analysis of the two alternative measurements of a firm's software inventive activities: software copyright and trademark filing.

Software Copyrights

Because copyright is non-patent intellectual property rights that allow a limited monopoly on technical ideas on software (Graham and Mowery, 2003), examining firms' software copyright filing activities can be another measure of their innovative activities for software development. The fact that the subject of software copyright protection is not a conceptual or mathematical algorithm, but program source code or the computer file itself makes the copyright filing a more straightforward measure of firms' software innovation activities.[23]

If the partial transfer of Novell patents did not associate with OIN members' overall

[23] See, the Circular 61 of the copyright law `https://www.copyright.gov/circs/circ61.pdf`

software innovation activities, their copyright filing intensity on new computer programs (or source code) is unlikely to have decreased after the partial transfer of the Novell patents. In contrast, if Novell's partial transfer of patents to the CPTN members negatively affected the overall software innovation activities by OIN members, their software copyright filing intensity should have dropped after the transfer.

To operationalize this test, I collect information about copyrights filed by OIN member companies from the US copyright office's database.[24] The copyright filing activities by MS becomes the baseline in this analysis because MS was not in the OIN program and was prevented from obtaining any of Novell patents by the regulation.[25] Then, I categorize copyright as software-copyright if the subject of the copyright is "computer program."

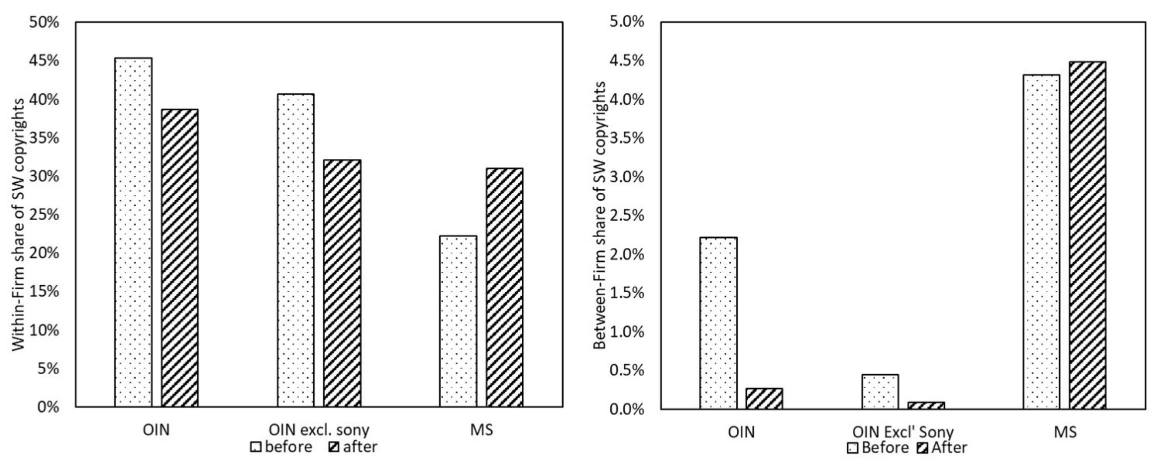


Figure 3.8: Analysis of Software-Copyright Filing Activities

The panel on the left of Figure 3.8 compares the Within-Firm share of software copyrights ($\frac{\#of SW copyrights}{\#of All copyrights}$) for the OIN members and MS each, before and after the partial transfer of Novell patents.[26] The comparison shows that OIN members' software copyright filing intensity decreased after the partial transfer of the Novell patents.

24 `https://cocatalog.loc.gov/cgi-bin/Pwebrecon.cgi?DB=local&PAGE=First`

25 I do not analyze the other CPTN members' copyright filing activities because the transfer of the Novell's patents to them could affect their copyright filing activities. Thus, the three CPTN members' copyright filing activities are not a proper baseline for the comparison.

26 Note that I take into account 1-year delay between the timing of copyright application and publication in counting the number of software copyrights as the delay in publishing copyright applications is two to 22 months (See the official note released by US copyright office in the following link `https://www.copyright.gov/registration/docs/processing-times-faqs.pdf`)

The panel on right presents the change in Between-Firm share of software copyrights that the OIN members and MS filed compared to the total number of software copyrights filed by the Top 100 software companies.[27] Similar to the within-firm software copyright share analysis, the OIN members' average share of software copyrights substantially reduced after the partial transfer of the Novell patents whereas MS did not.

Trademark Filing Activities

Firms' product or service innovation also can be measured by their trademark filing activities because trademark law protects products' brand name. Indeed, studies use trademark filing activities of firms to capture some aspects of firms' innovative activities (Mendonça et al., 2004; Srinivasan et al., 2008; Stoneman, 2010; Flikkema et al., 2014). If Novell's partial transfer of its patents to the CPTN members negatively affected OIN members' software innovation activities, their software trademark filing activities should have dropped after the transfer. I consider MS' trademark filing activities on software as a baseline in this analysis, as I did in the copyright filing analysis. I retrieve information of all the trademarks that were filed by the OIN members and MS from the USPTO trademark data (Graham et al., 2013).[28] I categorize a trademark as a "trademark on software" if the trademark document contains the clauses of "software for" or "computer program(s) for" in its goods and service description while being categorized into international class "009" ("Electrical and scientific apparatus").

Figure 3.9 presents the Within-Firm share of software trademarks (left) and Between-Firm share of software trademarks filed by the OIN members and MS. The data shows that the OIN members experienced decreased software-trademark filing activities after Novell's partial transfer of patents.

[27] in order of 2014 software sales revenue (https://www.pwc.com/gx/en/industries/technology/publications/global-100-software-leaders/explore-the-data.html

[28] Downloaded from https://www.uspto.gov/learning-and-resources/electronic-data-products/trademark-case-files-dataset-0

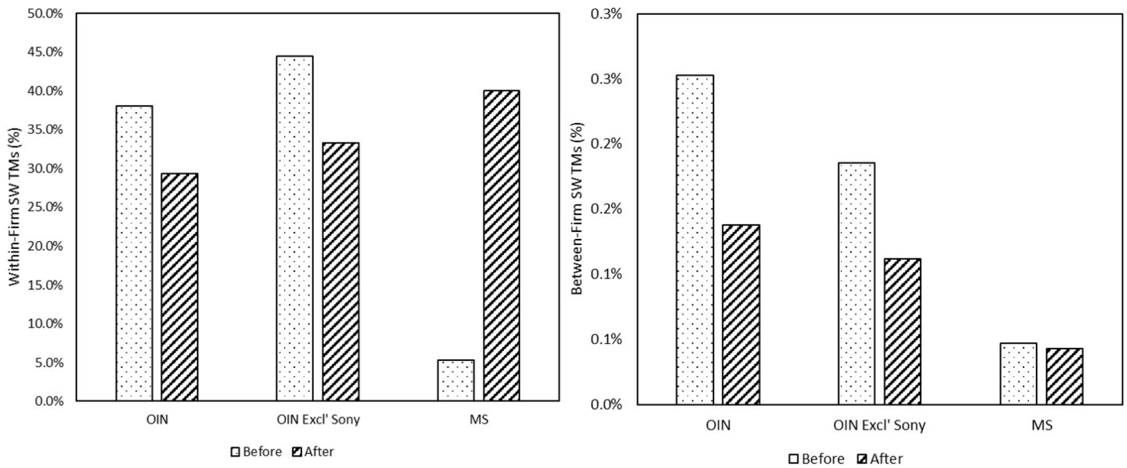


Figure 3.9: Analysis of Software-Trademark Filing Activities

In sum, my additional analysis using copyright and trademark data indicates that the CPTN member's consolidation of a part of Novell patents negatively affected the OIN members' software innovation activities.

3.6 Discussion and Conclusion

In this study, I examined how the antitrust regulation of patent-monopoly formation affects follow-on innovation. I focused on the the patent monopoly formation by a few firms' consolidation of existing patents. The constructed model in this study predicts that, in a sector where cumulative innovation is critical, a firm's consolidation of patents on substituting upstream technology for what it already possesses discourages the development of follow-on innovation by its market competitors. In contrast, it does not affect the patent-consolidating firm's development of follow-on innovation. The regulation of such patents consolidation is expected to positively affect the rate of the follow-on innovation of the market competitors while not affecting that of the patent consolidating firm.

I empirically tested the derived theoretical prediction by using the case of the US DoJ's partial regulation of Novell's software patents transfer to CPTN holdings in 2011. The member companies of the CPTN holdings (i.e., MS, Oracle, EMC, and Apple) were in intensive market competition with Linux-application vendors in the software market. In contrast, Novell was a key member of OIN that protects the Linux community from patent infringement disputes by sharing its software patents with the Linux community for free. Accordingly, it was believed that, after the patent transfer, the CPTN members may use the Novell patents to prevent the Linux software development to have a stronger market power in the software market. This antitrust concern led to the DoJ's intervention. DoJ restricted MS' patent acquisition only. The remaining Novell patents were transferred to the other CPTN members. By comparing the post-regulation number of follow-on inventions for the regulated- and transferred-patents, I tested my theoretical prediction.

My empirical analysis showed that the regulation positively affected OIN members' development of follow-on inventions. My additional analysis indicated that the regulation had mitigated the negative impact of CPTN members' consolidation of Novell patents on OIN members' follow-on inventions development. The analysis of software copyright and trademark filing trends found further supportive evidence of this conclusion. Yet, there was no evidence showing that the regulation affected CPTN members' follow-on inventions development. All in all, my study answers the question presented at the beginning of this paper: In the sector where cumulative innovation is crucial, regulating a firm's consolidations of patents on substituting upstream technologies for what it owns positively affects the follow-on innovation of its market competitors in the short-term.

Then, shouldn't the US DoJ have prohibited the transfer of all of the Novell patents in the first place? Does my finding imply that the regulation of patents consolidations is always necessary?

This study does not provide a complete answer. First, the DoJ's regulations primarily aim at encouraging "downstream market competition," rather than innovation. In contrast, the present study focused on the regulations' impact on the rate of follow-on innovation, not market competition. Because innovation and market competition are related but not the same dimension of social welfare, the overall impact of regulations on social welfare should not be dictated by the present study's findings. A more comprehensive analysis of how the regulations affected other dimensions of social welfare is necessary for a more inclusive conclusion.

Second, regulation of patent consolidation can even bring undesirable consequence to other dimensions of social welfare. In particular, when failing firms try to liquidate their patents and the only buyer of the patent is the patent consolidating firm, the government's restriction of such patent transfer deal may impose implicit exit-cost to the patent selling firm. The imposed exit-cost can damage the patent owner's appropriability by discounting the value of the patent, which also restricts the patent holder's enforceability. Because the restricted patent enforceability could attract the entry of less-efficient firms into the market (Gilbert and Shapiro, 1996), the regulation of the patent transfer deal may even result in reducing consumer welfare.

Regarding this undesirable effect of the regulation, one may suggest applying for the compulsory licensing regime as the solution; mandating the patent consolidating firms to license out the consolidated patents to market competitors. Yet, expecting the enforced compulsory license regime, the patent consolidating firm may not want to acquire the patents because the compulsory licensing essentially discounts the patent buyer's economic return of acquiring the patent. The reduced incentive to purchase the patent will take out the chance for the patent owner to sell their patents, accordingly.

The governmental acquisition of patents of failing firms can be a solution of this probable dilema (See Kremer, 1998). When a failing firm tries to sell its patents to a patent-consolidating firm, the government purchases the patents if the patents are critical to other's innovative activities. Through the government's patents acquisition, the patent seller obtains the salvage value of the patents to some extent (i.e., the ex-ante value of patent) while the government can ensure that the patents are not used to discourage follow-on innovative activities nor market competition. Later, the government can place on the patents on the public domain so that anyone can use the patented invention.

Third, it is necessary to consider whether promoting the development of follow-on innovation is always desirable from the social welfare standpoint. In some sectors, follow-on innovation used to end up with a marginal improvement of existing innovation. The development of follow-on innovation could easily result in duplication of R&D, which is socially sub-optimal (Gilbert and Newbery, 1982; Wright, 1983) in this case. In this study, I limited the case to a sector where the cumulative innovation is crucial and pervasive. However, it is not necessarily true in other sectors. Accordingly, whether antitrust regulations for promoting follow-on innovation is desirable for social welfare is a question that needs a careful understanding of the probable sectoral difference.

Finally, the decreased rate of follow-on innovation by the competitors of the patent-monopolist-to-be does not mean that their overall innovation is discouraged. The patent monopoly may change the direction of competitors' innovation. Examining whether and how regulations affect the direction of competitors' innovation is necessary for a more comprehensive understanding in this regard.

There could be some concerns about this study's empirical design. One issue is that the DoJ regulated not only the transfer of patents to MS but also EMC's attempt to acquire VM software patents. Because EMC's patent acquisition was partly regulated by the DoJ, one may argue that the patents ultimately acquired by EMC should be treated distinctively. My data does not support this argument. Although it is not definitive which patents could (or could not) be acquired by EMC, my manual investigation of the patent documents indicated that most VM patents were acquired by Oracle, not transferred back to Novell. Hence, I argue that the intervention into the transfer of VM patents was only intended to prevent EMC from acquiring these patents, not to completely prevent the consolidation of these patents by other CPTN members.

Another concern is that the constructed theoretical model is not comprehensive enough to capture a more general dynamics of patents transfer and the role of regulation in various situations. What if patented technologies in transfer are complementary rather than substitutes for what the patent buyers own? What if a follow-on innovation does not turn into a new product? How will the dynamics change if the patent buyer is a nonpracticing entity and, therefore, not in market operation? Although all these questions are relevant and intriguing, they are beyond the scope of the present study. I hope the constructed model in this study can serve as a useful theoretical foundation for future research to address further questions.

The present study makes two contributions. First, it elaborates on the current understanding of the relationship between antitrust and patent laws for innovation by demonstrating that the two institutions are not always complementary enterprises for innovation. Indeed, the patents can still create a market monopoly through patents consolidation and antitrust law works against it. The present study theoretically and empirically show the channel where antitrust intervention into the creation of a patent monopoly could positively affect the development of follow-on innovation.

Second, the finding that a firm's consolidation of existing patents through patents transfer may bring the antitrust issue while affecting innovation emphasizes the role of the antitrust authority in the market for patents. This implication also stresses the importance of extending scope of antitrust intervention from the typical business deal such as M&A to the "patents-only" transfer.

Table 3.5: Direction of the Regulation Impact

	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)
Regulated	0.0482	0.0467		0.0366	0.0359	
	(0.0528)	(0.0529)		(0.0578)	(0.0579)	
Transferred	**-0.0644****		**-0.0649****	-0.0289		-0.0289
	(0.0259)		**(0.0259)**	(0.0322)		(0.0323)
ln(PreCiteOIN+1)	0.357***	0.359***	0.357***			
	(0.00867)	(0.00875)	(0.00871)			
ln(PreCiteCPTN+1)				0.680***	0.681***	0.680***
				(0.00806)	(0.00812)	(0.00808)
nClaim	0.000818***	0.000851***	0.000808***	0.00175***	0.00178***	0.00175***
	(0.000240)	(0.000242)	(0.000240)	(0.000353)	(0.000356)	(0.000354)
DoJConcern	0.0313***	0.0317***	0.0324***	0.00423	0.00739	0.00467
	(0.00909)	(0.00918)	(0.00910)	(0.0121)	(0.0123)	(0.0122)
CiteOINPat	0.0249***	0.0243***	0.0237***	0.0736***	0.0737***	0.0740***
	(0.00635)	(0.00638)	(0.00636)	(0.00919)	(0.00926)	(0.00921)
CiteMSPat	0.0126*	0.0132**	0.0135**	0.0152	0.0155*	0.0147
	(0.00648)	(0.00652)	(0.00648)	(0.00930)	(0.00939)	(0.00933)
EuroFam	-0.00960	-0.00943	-0.00939	0.0475***	0.0497***	0.0478***
	(0.00736)	(0.00743)	(0.00737)	(0.0112)	(0.0114)	(0.0113)
Constant	0.0880	0.110	0.0907	-0.101	-0.0835	-0.0992
	(0.0861)	(0.0868)	(0.0873)	(0.0751)	(0.0759)	(0.0763)
R^2	0.189	0.191	0.189	0.418	0.419	0.418
Adjusted R^2	0.187	0.189	0.187	0.416	0.417	0.416
AppYrFE	Yes	Yes	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20089	19783	19963	20089	19783	19963

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Direction of the Regulation Impact-Textual Similarity Based Matching Group

	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)
Regulated	-0.0274	-0.0590		0.0393	0.00712	
	(0.0640)	(0.0924)		(0.0701)	(0.0974)	
Transferred	**-0.135*****		**-0.117*****	0.0381		0.0391
	(0.0413)		**(0.0435)**	(0.0448)		(0.0468)
ln(PreCiteOIN+1)	0.383***	0.365***	0.388***			
	(0.0424)	(0.0866)	(0.0487)			
ln(PreCiteCPTN+1)				0.707***	0.733***	0.694***
				(0.0372)	(0.0722)	(0.0422)
nClaim	0.000657	0.00323	-0.0000249	0.00171	-0.00171	0.00257
	(0.00161)	(0.00385)	(0.00177)	(0.00186)	(0.00445)	(0.00202)
DoJConcern	0.0566	-0.0559	0.0917*	-0.0671	0.0452	-0.101**
	(0.0499)	(0.114)	(0.0539)	(0.0450)	(0.105)	(0.0513)
CiteOINPat	0.129***	0.334***	0.0810	0.0119	0.0873	-0.0219
	(0.0444)	(0.0961)	(0.0511)	(0.0482)	(0.0905)	(0.0586)
CiteMSPat	-0.0501	-0.0230	-0.0407	0.0195	0.00698	0.0197
	(0.0436)	(0.115)	(0.0478)	(0.0451)	(0.102)	(0.0524)
EuroFam	0.0708	0.145	0.0743	-0.000346	-0.0491	0.00692
	(0.0517)	(0.144)	(0.0559)	(0.0472)	(0.0996)	(0.0552)
Constant	-0.463**	0.0255	-0.383*	-0.553**	0.0589	-0.509**
	(0.218)	(0.168)	(0.216)	(0.264)	(0.144)	(0.236)
R^2	0.250	0.320	0.270	0.528	0.553	0.533
Adjusted R^2	0.212	0.199	0.223	0.504	0.474	0.503
AppYrFE	Yes	Yes	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	740	206	534	740	206	534

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Test with Alternative Control Group (AOL-MS vs. Novell's patents)

	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)	ln(PostCiteCPTN+1)
Regulated	**0.181****	**0.324*****		-0.0239	-0.161	
	(0.0816)	**(0.105)**		(0.100)	(0.135)	
Transferred	0.0103		-0.0279	-0.0228		-0.00154
	(0.0581)		(0.0571)	(0.0805)		(0.0824)
ln(PreCiteOIN+1)	0.328***	0.349***	0.301***			
	(0.0508)	(0.0807)	(0.0598)			
ln(PreCiteCPTN+1)				0.615***	0.646***	0.601***
				(0.0495)	(0.0880)	(0.0500)
nClaim	-0.000763	0.00128	-0.00144	0.000548	-0.000613	0.00000956
	(0.00114)	(0.00154)	(0.00106)	(0.00170)	(0.00240)	(0.00173)
DoJConcern	0.0154	-0.101	0.0447	-0.127**	-0.0892	-0.137**
	(0.0566)	(0.126)	(0.0590)	(0.0600)	(0.138)	(0.0654)
CiteOINPat	0.0375	0.0918	-0.0115	0.0297	-0.00170	0.0547
	(0.0484)	(0.0794)	(0.0545)	(0.0612)	(0.105)	(0.0714)
CiteMSPat	-0.0143	-0.106	-0.00106	0.0221	0.0656	0.0229
	(0.0471)	(0.0944)	(0.0490)	(0.0522)	(0.0982)	(0.0585)
EuroFam	0.0225	0.105	0.0556	-0.0282	-0.0920	-0.0378
	(0.0562)	(0.109)	(0.0557)	(0.0642)	(0.124)	(0.0710)
Constant	-0.430**	-0.349**	-0.218	-0.388	0.215	-0.365
	(0.181)	(0.138)	(0.190)	(0.265)	(0.176)	(0.273)
R^2	0.193	0.297	0.170	0.447	0.516	0.445
Adjusted R^2	0.139	0.174	0.104	0.409	0.432	0.401
AppYrFE	Yes	Yes	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	522	216	396	522	216	396

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Rate of Microsoft's Follow-on Inventions

	ln(PostCiteMS+1)	ln(PostCiteMS+1)
Regulated	-0.00117	0.0418
	(0.0449)	(0.0377)
ln(PreCiteMS+1)	0.483***	0.518***
	(0.0425)	(0.0668)
nClaim	0.00309	0.00269
	(0.00207)	(0.00213)
DoJConcern	-0.150***	-0.0767
	(0.0425)	(0.0505)
CiteOINPat	-0.00901	-0.00181
	(0.0564)	(0.0436)
CiteMSPat	0.0140	0.0129
	(0.0423)	(0.0500)
EuroFam	0.0177	-0.00557
	(0.0610)	(0.0781)
Constant	-0.302*	-0.216
	(0.161)	(0.138)
Sample	*regulated* vs. *transferred*	*regulated* vs. *leftover*
R^2	0.384	0.543
Adjusted R^2	0.336	0.478
AppYrFE	Yes	Yes
TechFE	Yes	Yes
Observations	432	250

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 4

GRANTING A FIRM EXCLUSIVE ACCESS TO A UNIVERSITY'S INVENTIONS AND ITS EFFECT ON THE RATE OF FOLLOW-ON INNOVATION

In the research policy domain, a prominent question has been whether granting a firm the exclusive rights to use a university's inventions deters innovation by restricting other's access to scientific knowledge or if it encourages innovative activities around the university's inventions by prompting the recipient to invest in R&D for follow-on innovation.

The present study explores the answers to this question by examining whether giving a firm exclusive access to a university's inventions encourages the recipient's follow-on invention, if there is positive externality for non-recipients' innovative activities, and if its probable benefits for a follow-on invention are marginalized when a university's invention is characterized as a scientific common. I consider patent title transfer from a university to a firm the enabling of exclusive access to the university's invention for the patent-acquiring firm.

After examining US patents that were transferred by 107 research-intensive US universities to firms between 2000 and 2013, I found no evidence that recipients became more active in developing follow-on inventions after acquiring the university's patents. However, it does promote follow-on inventions by non-recipients. Further analysis found no evidence showing that enabling exclusive access to a university's inventions in scientific commons marginalizes this positive association.

This research contributes to elucidating the consequences of exclusive access to university inventions for follow-on invention and to shedding light on the less-recognized role of the university in the innovation system: supplier for the patent market.

4.1 Introduction

University research has been one of the prominent subjects of public policy support because they frequently serve a locus of basic scientific research (National Science Foundation, 2002; National Science Board, 2012) which used to become the key foundation for technological innovation (Jaffe, 1989; Mowery and Nelson, 1999; Mowery and Sampat, 2005; Berman, 2011). The use of the OncoMouse, developed by Harvard University researchers, as an essential tool in cancer treatment research (Stewart et al., 1984; Blaug et al., 2004; Murray, 2010) is a well-known example of how the university's inventions stemming from their scientific research can be crucial technological inputs for further innovation. Because of such unique positioning of universities in the knowledge-based economy, the government provides public research funding and institutional support for university scientific research.

Yet, utilization of a university's invention is unlikely to be efficient for two-sided incentive problems. First, university inventions are often too embryonic to be utilized as is (Jensen and Thursby, 2001; Thursby et al., 2001); therefore, they require the recipients to make an extensive additional R&D investment for the commercialization of the invention. This raises the recipient's appropriability concerns (Colyvas et al., 2002; Motohashi, 2005) because if the return on the recipient's R&D investment is not protected, the incentive for moving ahead is substantially removed (Arrow, 1962). Second, the engagement of the university's researchers is critical for successful commercialization of the university's invention (Jensen and Thursby, 2001; Thursby and Thursby, 2003; Goldfarb and Henrekson, 2003). However, there is no substantive economic incentive for the academic researchers to become engaged in such an endeavor because, without proper institutions, the successful commercialization of the university's inventions does not necessarily provide economic benefit to the researchers.

This two-sided incentive problem has served as the necessity for and the key foundation of the establishment of formal institutions that enable exclusive access by firms to a university's inventions (see Mowery and Sampat, 2005; Thursby and Thursby, 2007; Shapira and Youtie, 2010). Allowing universities to own intellectual property right on federally funded research (i.e., Bayh-Dole Act) and the practice of exclusive licensing are examples (see Jensen and Thursby, 2001; Feldman et al., 2002). Such institutions were expected to mitigate the recipient's appropriability concern while creating an economic incentive for academic researchers to more actively engage in commercializing the research outcomes by tying their private economic benefit to the results of commercialization of the research outcomes (Jensen and Thursby, 2001; Thursby and Thursby, 2003).

These institutional benefits were expected to promote, in particular, follow-on innovative activities around the university's inventions. First, as intended, giving exclusive access to the university's inventions can address the recipients' appropriability concerns, and thus promote their R&D investment for follow-on invention. Second, doing so can encourage other's subsequent inventions by indicating the arriaval of new technological opportunities (Larsen, 2011; Drivas et al., 2017; Thompson et al., 2018). This anticipated positive externality can be even further promoted by mutual learning among the innovators from each other's innovative activities (Jaffe, 1986; Patel and Pavitt, 1995; Griliches, 1995).

In contrast, enabling exclusive excess to a university's inventions has been criticized for its probable consequence of slowing down scientific progress and innovation by generating the problem of so-called "privatization of scientific commons" (Partha and David, 1994; Argyres and Liebeskind, 1998) or aggravating the "tragedy of anti-commons"(Heller and Eisenberg, 1998; David et al., 2000; David, 2004; Nelson, 2004; Walsh et al., 2007). A well-known example that illustrates this concern is what happned after the exclusive license of the OncoMouse patent to DuPont. After DuPont acquired the exclusive right to use the OncoMouse, it started to restrict the OncoMouse enabled scientific research and commercial activities (Murray, 2006).

This concern becomes even more salient when considering that a university's research is often publicly funded to promote the creation of scientific knowledge that can bring about a broad socioeconomic impact. Indeed, the government provides public research funding to universities to promote their basic scientific research (Shapira and Youtie, 2010), the outcome of which can become part of the scientific commons. Hence, enabling exclusive access to a university's scientific discoveries can significantly impede scientists' ability to conduct further research (David, 2004; Andrews et al., 2006), which also results in the discouragement of subsequent innovative activities (Merges and Nelson, 1990; Scotchmer, 1991; Williams, 2013) or diffusion of knowledge (Sampat, 2004; Murray and Stern, 2007).

The arguments summarized above imply that granting a firm the exclusive right to use a university's inventions may have differential impacts on the development of subsequent inventions by entity and nature of the underlying knowledge. It could promote more the recipient's innovative activity around the university's invention while also encouraging that of non-recipients for the probable positive externality. However, enabling exclusive access for one firm to the university's inventions that are in the scientific commons is expected to marginalize that positive impact.

The present study aims to empirically explore these probable differential impacts. My empirical strategy is based on the transfer of ownership of a university's patents to firms. After the patent ownership transfer, the recipient becomes to secure the exclusive right to use the patented invention. In comparison to patent licensing, where the original patent owner retains ownership of the patent and has discretion in the use of the invention to some extent, a patent transfer is a more definitive way of conferring exclusive access to the knowledge in the patent.

By virtue of the fact that scientific commons have been largely the product of publicly funded research (Nelson, 2004), and universities often conduct basic scientific research using public funding, I consider a university's inventions based on the outcomes of federally sponsored research to be containers of the scientific commons.

My data consists of US patents granted to 107 research-intensive US universities who then transfer those patents to outside firms between 2000 and 2013. My analysis finds no evidence showing that the recipient of university's patents become more likely to engage in the development of follow-on inventions. However, the patent transfer does positively affect the development of subsequent inventions by the non-recipients of the university's patents. Interestingly, there is no evidence showing that conferring a firm exclusive access to a university's invention that is characterized as the scientific common marginalizes this positive association.

The contribution of this study is twofold. First, my research advances the recent scholarly efforts toward empirically examining the impact of enabling exclusive access to universities' knowledge on innovation. The contribution lies in the fact that this study directly examines the impact of privatization of universities' inventions that are featured as scientific commons and investigates its impact on the rate of follow-on innovation more comprehensively than use of a few universities' practice of exclusive patent licensing (e.g., Sampat and Ziedonis, 2004; Murray and Stern, 2007; Drivas et al., 2017; Thompson et al., 2018). Second, this study also extends the conventional understanding of a university's role in the National Innovation System (NIS) (Edquist, 2013, 2010; Lundvall, 2010; Mowery and Sampat, 2005; Youtie and Shapira, 2008) by shedding light on the relatively less-explored role of universities as suppliers to the patent market. In doing so, this study contributes to the recently growing literature on the market for patents and how it shapes innovation (Ciaramella et al., 2017; Hochberg et al., 2018; Serrano and Ziedonis, 2018; Kwon, 2018).

The remainder of this paper is structured as follows. In Section 2, I provide my review of prior studies on the impact of granting a firm the exclusive access to a university's inventions, focusing on the literature about the tragedy of the anti-commons as well as the issue of the privatization of the scientific commons. From this review, I derived my three main hypotheses. In Section 3, I describe the empirical strategy and data used for testing the hypotheses. Section 4 presents the findings, and their implications are discussed in Section 5. Section 6 concludes the paper with a discussion of the present study's limitations and future research opportunities.

4.2 Literature Review and Hypotheses

It has been argued that granting a firm the exclusive access to a university's inventions is essential for the efficient technology transfer and its commercialization.

First, the exclusive right to use a university's inventions is necessary to incentivize commercialization of universities' knowledge (see Mowery and Sampat, 2005; Thursby and Thursby, 2007; Shapira and Youtie, 2010). For successful utilization of a university's invention, the involvement of the university's researchers in the commercialization process is crucial (Jensen and Thursby, 2001; Thursby and Thursby, 2003; Goldfarb and Henrekson, 2003). Allowing the researchers to own the patents, and therefore have the ability to license the use of the invention, is one way of incentivizing researchers to participate in the commercialization effort because the revenue generated from successful commercialization benefits the academic researchers. Indeed, a study by Friedman and Silberman (2003) found that rewarding university researchers in such a manner helps expedite the transfer of the university's technologies.

Second, granting a firm the exclusive access to a university's invention mitigates the recipient's appropriability concerns. A case study by Colyvas et al. (2002) elaborated on the importance of concerns about appropriability with regard to transferring a university's inventions. The study showed that if the invention in question is too embryonic, the recipients of rights to use the invention should invest extensively in additional R&D for commercialization. If the invention is not exclusively accessible, the return on such private R&D investment can be easily stipulated by a competitor's probable imitation. Hence, these firms prefer to receive exclusive rights to use the invention. Given that a university's inventions are often too embryonic to be commercialized as they are (Jensen and Thursby, 2001; Thursby et al., 2001), the appropriability concern of a potential recipient of the university's inventions could be particularly salient. A study by Bercovitz and Feldman (2007) empirically confirmed that when a university's research can be fully appropriated, the recipient firms consider the university to be a partner. By using MIT's patent license data, Shane (2002) showed that university patents are more likely to be licensed when patent protection is effective. In addition, the licensing revenue is positively associated with the degree of effectiveness of patent protection. These findings indicate that exclusivity in the use of a university's inventions matters to firms.

To summarize, granting a firm the exclusive access to a university's inventions mitigates the appropriability concerns of the recipient, which in turn, encourages the recipient's innovative activity around the university's inventions. This forms the basis of my first hypothesis:

Hypothesis 1. Granting a firm the exclusive access to a university's invention encourages the recipient to develop subsequent inventions.

Enabling exclusive access to a university's invention may impose positive externality. When a university confers exclusive right to use an invention to an outside firm, it can signal an emerging technological opportunity to the rest of the stakeholders in that field of endeavor (Drivas et al., 2017; Thompson et al., 2018), which may encourage innovative activities around the university's inventions overall. Because innovators learn from each other's work (see, Jaffe, 1986; Patel and Pavitt, 1995; Griliches, 1995), the invigorated innovative activities and the outcomes could come to serve as intellectual inputs for further innovative activities around the university's inventions. The probable presence of the positive externality is formulated into the second hypothesis:

Hypothesis 2. Granting a firm the exclusive access to a university's inventions encourages the development of follow-on inventions by non-recipients.

Granting a firm the exclusive access to a university's inventions may, however, discourage open science and slow down scientific progress. This is particularly pertinent given the fact that universities often conduct basic scientific research using public money. Exclusive access for a firm to the inventions that are the outcome of publicly funded scientific research may restrict the broad utilization of the inventions by others. The body of literature regarding the tragedy of the anti-commons hints that exclusive access to a university's scientific commons inventions can hold up future research by restricting the flow of knowledge that would lead to the next steps in research and innovation (Heller and Eisenberg, 1998; Argyres and Liebeskind, 1998; David et al., 2005). Indeed, Walsh et al. (2007) and Thompson et al. (2018) find empirical evidence that denial of access to inputs for scientific research significantly delays future scientific work.

This concern has also been expressed with regard to the practice of exclusive licensing of a university's inventions (Nelson, 2004). When a university exclusively licenses its inventions to a firm, it can be particularly detrimental to the development of follow-on innovations by non-licensees if the invention is the outcome of scientific research that was publicly funded. Given that among the stated missions of public research funding are the promotion of basic science, diffusion of knowledge, and encouragement to utilize the outcomes for innovation, granting a firm the exclusive access to a university's inventions that are characterized as the part of the scientific commons can be seen as misaligned with the stated goal of the research policy.

A series of studies support this claim. Feldman et al. (2007) stated that one of the factors leading to the successful utilization of the Cohen-Boyer DNA splicing technology was the practical, flexible, and *less restrictive* licensing program used by Stanford University and the University of California. Studies by Sampat (2004) and Murray and Stern (2007) contended that exclusive access to scientific knowledge through patenting does, indeed, squelch follow-on scientific research. They backed up their contention with the finding that citations to scientific publications were significantly reduced after the granting of the corresponding patents. By analyzing the case of patents licensed by the University of California, Thompson et al. (2018) also made the case that licensing of a university's patented research tool restricts follow-on scientific research.

Given that the government provides public money to universities to support their scientific research, the university's granting of exclusive access to inventions that are the result of publicly funded research can generate the so-called privatization of the scientific commons (Nelson, 2004), which may deprive the benefits of enabling exclusive access in the development of follow-on inventions.

Yet, this argument could be challenged because privatization of a university's scientific knowledge occurs when the university patents on it. By the Bayh-Dole act, the university becomes to own the "exclusive right to use" its invention even if it was developed using the public money once the university patent on the invention. Accordingly, granting a firm the exclusive access to the university's inventions originated from the public research funding may not generate nor aggravate the "privatization of scientific common" effect as long as the invention has been patented. This discussion is distilled into the third hypothesis:

Hypothesis 3. Granting a firm the exclusive access to a university's inventions that are in the scientific commons may (or may not) marginalize its positive effect on the development of follow-on inventions.

Figure 4.1 illustrates the three hypotheses. In the next section, I describe the empirical strategy and data I used to test the derived hypotheses.

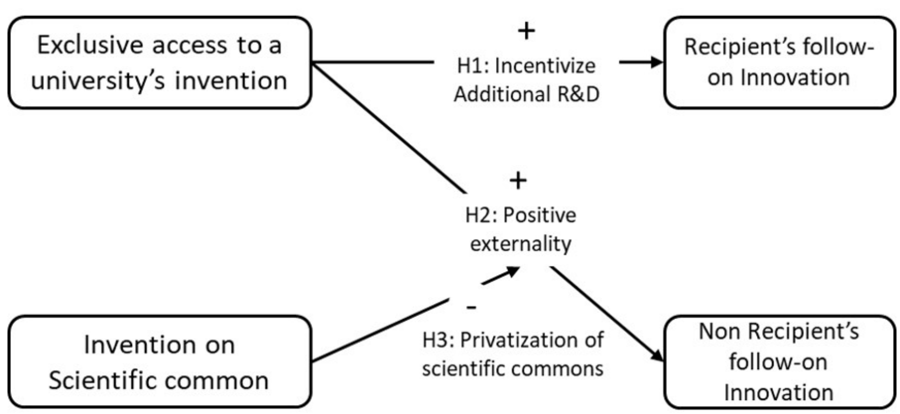


Figure 4.1: Hypotheses

4.3 Empirical Analysis

4.3.1 Data and Descriptive Analysis

The empirical work of the present study is based on the transfer of patent titles from research-intensive universities to outside firms. By transferring ownership of the patent, the recipient comes to have exclusive right to use the university's patented invention.

My data consists of US patents granted to research-intensive US universities who then transfer the patents ownership to outside firms (hereafter univ-transferred patents). To identify research-intensive universities, I first pull a list of R1 and R2 universities from the Carnegie Classification Data Collection.[1] Multiple campuses that are part of a larger university umbrella system using the same base university name are merged into one.[2]

Next, by using the USPTO's patent assignment database (Graham et al., 2018), I obtain a list of US patents of which those universities transferred to an outside firm between 2000 and 2013.[3] Then, I search for detailed information on these patents using the data provided by patentsview.org.[4] To screen out patents that were transferred by ex-ante contract (i.e., a patent that was transferred before the patent existed), all patents that were transferred to an outside firm before or on the patent application date were excluded from the sample (see Serrano and Ziedonis, 2018).

According to the collected data, 107 research-intensive US universities have transferred at least one US patent to outside firms, with a total of 913 univ-transferred patents. The University of California took first place for the number of patents transferred (102), followed

[1] I used 2015 data because it was the most up-to-date available at the time I conducted this research. The full list of universities is available at `http://carnegieclassifications.iu.edu/downloads/CCIHE2015-PublicDataFile.xlsx`.

[2] For example, University of California campuses in Berkeley, Irvine, Davis, and Los Angeles were combined into "University of California." This merging process was necessary due to intellectual property assets of multi-campus universities being managed by the same TLO or advisory board.

[3] I use the patent forward citation as the key dependent variable in the regression analysis. To have at least five years of forward citation observation point following a patent transfer (the latest year for patent forward citations in the data set was 2017), I limit the patents to those transferred before 2014.

[4] Publicly provided by USPTO.

by the University of Texas (68 patents). Figure 4.2 displays the number of univ-transferred patents by the top 20 universities.

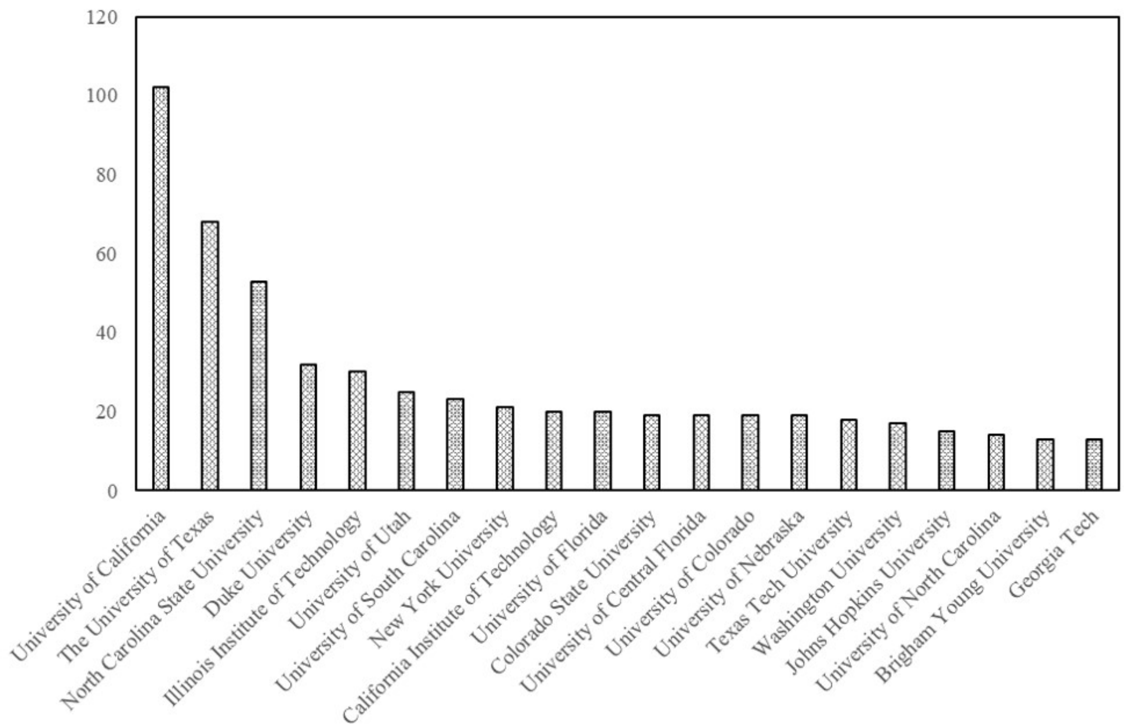


Figure 4.2: Top 20 universities (Number of transferred patents to firms)

To operationalize the definition of an invention as part of the scientific commons, I capitalize on the fact that the university's scientific researches with extensive public value are often awarded governmental research funding. That is, I consider a patent on the outcome of federally funded research to be a proxy for the invention being in the scientific commons. To identify such patents, I make use of federal regulations that universities must state the federal funding agency for their patent if the patent originated from the federal funding ("statement of government interest"; Section 202(c) of the Bayh-Dole Act covering university ownership of a patent resulting from federally funded research). Accordingly, I code patents as inventions in the scientific commons if they contain the statement of government interest (hereafter FEDs; non-FEDs for patents that had no statement of government interest). Out of the 913 patents in the sample, 214 (23.4%) were FEDs.[5]

[5] One may argue that this operationalization may not be an accurate way of identifying the patents on

Figure 4.3 profiles the National Bureau of Economic Research (NBER) categories (Hall et al., 2001) for the univ-transferred patents. *Drugs & Medical* is the most populated technology field for both FEDs (28%) and non-FEDs (38.5%). *Chemical* and *Electric* are the second most populated fields for, respectively, FEDs (21%) and non-FEDs (21%).

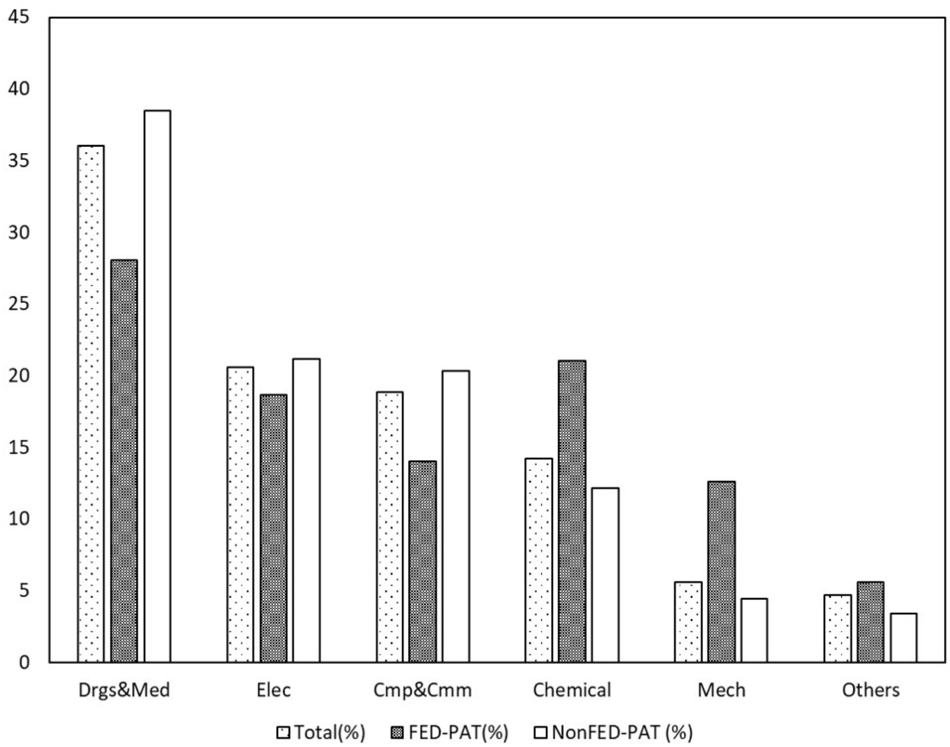
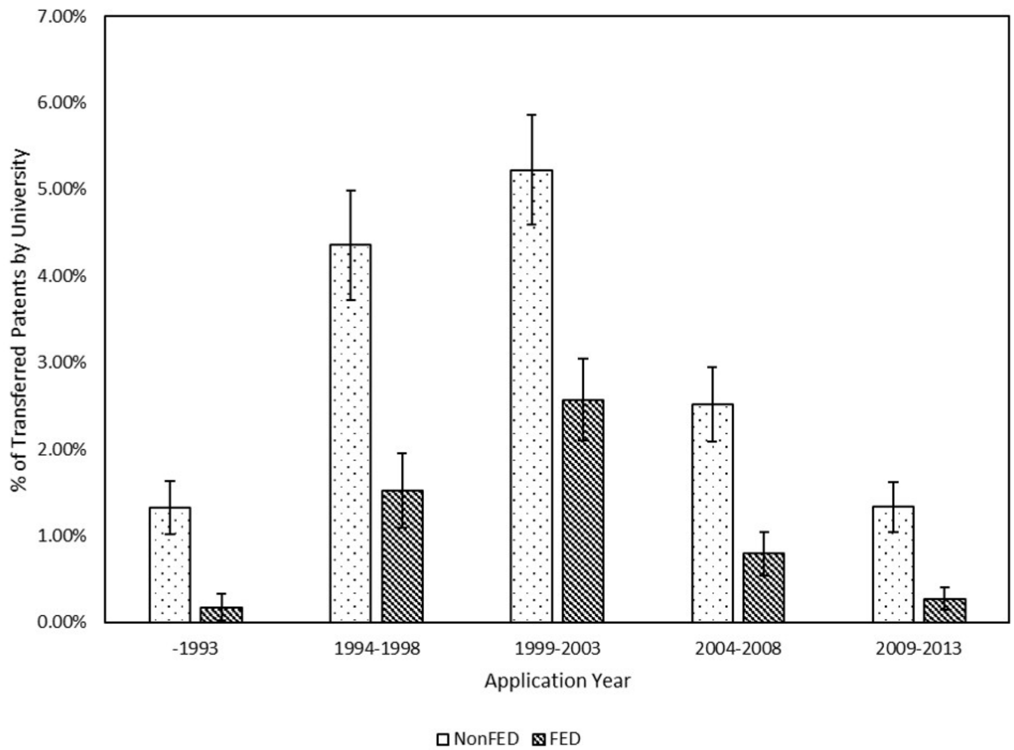


Figure 4.3: Technology Class Distribution

I explore how likely it was for FEDs to be transferred to an outside firm as compared to non-FEDs, by using the information about patents owned by 107 universities where ownership had not changed between 2000 and 2013. The overall proportion of FEDs transferred to outside firms is lower than non-FEDs, on average. Among FEDs (22,196), only 214 patents (0.96%) were transferred to outside firms, whereas about 2.64% of non-FEDs were transferred to outside firms. This difference consistently holds over the different periods,

outcomes of "publicly funded" research because there are many more ways that public funding is provided to universities than just the federal government's research program. However, given that federal research funding is the primary source in many cases and it is the best available way of identifying the origin of governmental support at the patent level, this operationalization can be still useful.

as shown in Figure 4.4.



Error bars present 95% confidence intervals obtained from the t-tests

Figure 4.4: Share of Univ-Transferred Patents by Application Year

This finding indicates that FEDs might have been systematically less targeted for acquisition by firms, or universities might be less willing to transfer them than non-FEDs.

To explore whether there is a distinctive difference in the timing of a transfer between FEDs and non-FEDs, I visually compare the distribution of the time to transfer by year between FEDs and non-FEDs, as shown in Figure 4.5.

The average time to transfer for FEDs is 4 years while for non-FEDs, it is 6 years. The distribution patterns for both FEDs and non-FEDs display decreasing frequency with the age of a patent (counted in the number of years between the transfer date and the application date).

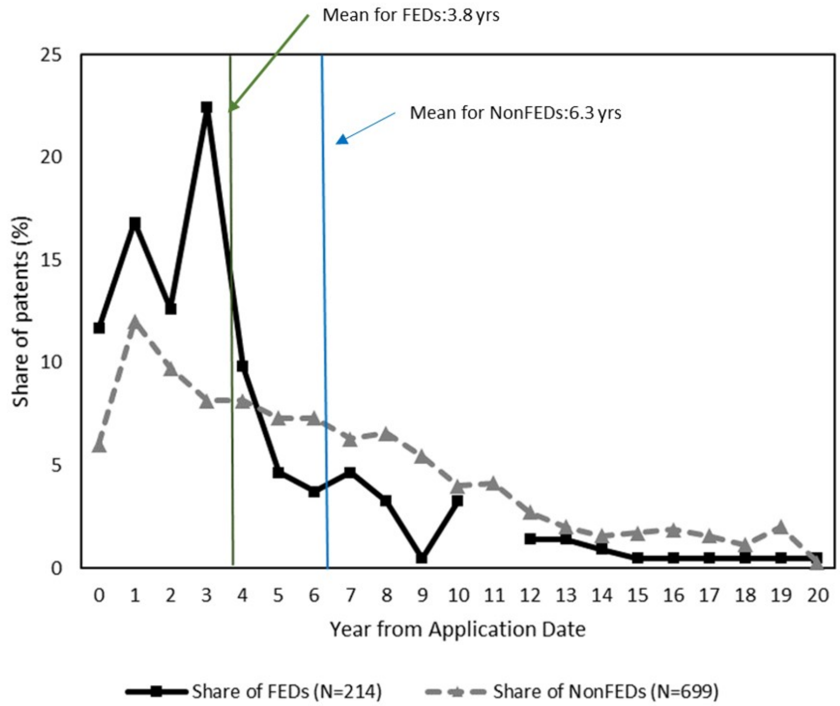


Figure 4.5: Distribution of Time to Transfer (by Year)

4.3.2 Econometric Model

My identification strategy is based on the variation in the timing of patent transfer using the same method that Drivas et al. (2017) employed to analyze the impact of universities' exclusive licensing on the rate of follow-on inventions.

I employ the number of citations that a patent received from consecutive patents (i.e., forward citation) as a proxy for the number of follow-on inventions of the focal patent (Jaffe et al., 1993; Galasso and Schankerman, 2014; Gaessler et al., 2017; Drivas et al., 2017). The more the forward citations a patent received, the greater the extent of subsequent inventive activities around the focal patented invention. The natural log value of the forward citations that an univ-transferred patent received in period s counted at the calendar year t plus 1 was the dependent variable. Suppose that patent *i* filed in 2011 received 10 patent citations in 2015. Then, the dependent variable takes the value of $ln(FWD_{i,4,2015} + 1) = ln11$ for this data point. For each patent, I count the forward citations for each year up to either

December 31, 2017[6] or its statutory expiration date (i.e., 20 years from its application date).[7]

For the purpose of the present research, I use the three forward citation indicators as the dependent variables: total number of forward citations ($FWDAll$, proxy for the total number of follow-on inventions), forward citations made by the patent recipient ($FWDInt$, proxy for the number of follow-on inventions developed by the recipient of the university's patent), and forward citations made by non-recipients of the patent ($FWDExt$, proxy for the number of follow-on inventions developed by those who had no access to the focal invention).

The independent variable is $PostTransfer_{i,s}$, which takes the value of 1 if the patent of interest was transferred to a firm in period s, and 0 otherwise. If a patent filed in 2000 was transferred to a firm in 2010, $PostTransfer_{i,s}$ took the value of 1 for all $s \geq 11$.

In this research design, the counterfactual is how many patent citations an univ-transferred patent might have received if the patent had not been transferred to a firm. Because this is not observable, I utilize the variation in timing of the patent's transfer as Drivas et al. (2017) employed. Suppose there are two patents. One was filed in 2000 and transferred to a firm in 2005. The other was filed in 2000 and transferred to a firm in 2010. I used the forward citations that the later transferred patent received from 2005 to 2010 as the proxy for the counterfactual of the forward citations that the early transferred patent might have received from 2005 to 2010.

To take into account variations in the dependent variable by time-invariant characteristics of the patent, I use a patent-level fixed effect (FE) estimator.[8] I also control for the FE of the calendar year when the forward citations were made (i.e., dummy variables for that year) to account for the probable effect of secular time events on the rate of follow-on

6 The patent citation data covers patents filed up to December 31, 2017.

7 The analysis using the actual expiry date is reported in the robustness check section.

8 In the robustness check section, I discuss whether the FE estimator is appropriate to use by reporting the Hausman test result.

inventions.[9] I use the cluster-robust standard error, by university, to take into account intra-school correlation in the error terms. To test Hypothesis 1 and 2, I regress my data on the following econometric model specification:

$$ln(FWDY_{i,s,t} + 1) = \beta_0 + \beta_1 \times PostTrans_{i,s} + Patent_i + Period_s + Year_t + \epsilon_{i,s,t} \tag{4.1}$$

where $FWDY_{i,s,t}$ is $\{FWDAll, FWDInt, FWDExt\}$, $Patent_i$ is the patent FE, $Period_s$ captures period FE, $Year_t$ captures the calendar year FE, s is the number of years since the patent application date ($s \in [1, max(20, YearMax)]$), $YearMax$ is the number of years between the patent application date and December 31, 2017, and $\epsilon_{i,s,t}$ is error term.

Hypothesis 1 expects β_1 to take a positive and statistically significant value when $ln(FWDInt+1)$ is the dependent variable. When the dependent variable is $ln(FWDExt+1)$, β_1 takes a positive and statistically significant value if Hypothesis 2 is supported. If Hypotheses 1 and 2 are both supported, β_1 is expected to take a positive and statistically significant value if $ln(FWDAll + 1)$ is the dependent variable.

To test Hypothesis 3, I introduce the interaction term between FED_i (which was 1 for FEDs) and $PostTransfer_{i,s}$. The following is the econometric model specification:

$$\begin{aligned} ln(FWDY_{i,s,t} + 1) = \beta_0 + \beta_1 \times PostTransfer_{i,s} + \beta_2 \times FED_i \times PostTransfer_{i,s} \\ + Patent_i + Period_s + Year_t + \epsilon_{i,s,t} \end{aligned} \tag{4.2}$$

Hypothesis 3 expects a negative and statistically significant value of β_2 if $ln(FWDExt+1)$ is the dependent variable. The counterargument expects to fail to reject the null hypothesis.

[9] For example, rapid emergence of a new technological opportunity by an exogenous event in a particular year could lead to a substantial increase in forward citations to a prior patent related to the technology.

4.4 Results

4.4.1 Main Regression

Table 4.1 reports the main regression results, where the first three columns use $ln(FWDAll+1)$, $ln(FWDInt+1)$, and $ln(FWDExt+1)$ as the respective dependent variables. The independent variable is $PostTransfer$.

Table 4.1: OLS regression with Patent Fixed Effect

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.133***	-0.0179	0.146***	0.135***	-0.0196	0.147***
	(0.0416)	(0.0174)	(0.0377)	(0.0452)	(0.0188)	(0.0403)
FEDxPostTransfer				-0.00542	0.00817	-0.00504
				(0.0515)	(0.0194)	(0.0502)
Constant	-0.524***	0.0273	-0.546***	0.575***	0.0268	0.553***
	(0.112)	(0.0176)	(0.109)	(0.110)	(0.0175)	(0.107)
R^2	0.118	0.021	0.109	0.118	0.021	0.109
Adjusted R^2	0.116	0.019	0.107	0.116	0.019	0.106
Observations	14054	14054	14054	14054	14054	14054

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the first column, we see that the coefficient $PostTansfer$ is positive and statistically significant at the 0.01 significance level (0.133). This indicates that, on average, the total number of follow-on inventions of the univ-transferred patent increases by 13.3% after the university transfers the patent. The second column shows that the coefficient $PostTransfer$ is not statistically significant at the 0.1 significance level. There is no evidence indicating that a patent recipient's inventive activity around a university's patent is affected by the patent transfer.

The coefficient $PostTransfer$ in the third column is positive and statistically significant at the 0.01 significance level (0.146). On average, the number of non-recipients' follow-on inventions of a university's patent increases by 14.6% after the patent is transferred. This supports Hypothesis 2.

Columns 4 through 6 report the regression results with the interaction term between FED_i and $PostTransfer_{i,s}$. In the fourth column, the coefficient $FED \times PostTransfer$

is statistically insignificant at the 0.1 significance level. There is no evidence showing that granting a firm exclusive right to use a university's invention in a part of scientific commons marginalizes its positive effect on the development of follow-on inventions.

The fifth column reports the regression result using $ln(FWDInt+1)$ as the dependent variable. Both the coefficients $PostTransfer$ and $FED \times PostTransfer$ are statistically insignificant at the 0.1 significance level. In the sixth column, the coefficient $FED \times PostTransfer$ is statistically insignificant at the 0.1 significance level. The regression results indicate that there is no evidence supporting Hypothesis 3.

All in all, my regression analysis does not find evidence for Hypothesis 1 and 3. However, there is evidence showing that granting a firm the exclusive access to a university's inventions through patent transfers encourages non-recipients to develop follow-on inventions (Hypothesis 2 is supported).

4.4.2 Robustness Check

Use of random effect (RE) estimator

I use the hausman test (Hausman, 1978) to determine if the FE estimator is an appropriate primary estimator. If both the FE and RE estimators are mutually consistent, the RE estimator is preferred because it is more efficient. Otherwise, the FE estimator is used. Table 4.2 presents the RE regression and Hausman test results. Overall, the statistical significance and sign of the coefficients of the independent variables are consistent with those of the FE model regression. The calculated p-values with χ^2 from the Hausman test when $ln(FWDAll + 1)$ and $ln(FWDExt + 1)$ are the dependent variables is less than 0.05, and it is insignificant at the 0.1 significance level, when the dependent variable is $ln(FWDInt + 1)$. This indicates that the FE estimator is appropriate for regressing $ln(FWDAll+1)$ and $ln(FWDExt+1)$ whereas the RE was proper to use when regressing $ln(FWDInt + 1)$. Overall, the selection of the estimator does not change the main findings.

Table 4.2: OLS panel regression with Random Effect and Hausman-Test result

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.135***	-0.0268	0.153***	0.150***	-0.0265	0.168***
	(0.0427)	(0.0197)	(0.0385)	(0.0472)	(0.0204)	(0.0423)
FEDxPostTransfer				-0.0702	-0.00156	-0.0661
				(0.0505)	(0.0179)	(0.0484)
Constant	-0.0759	0.0248	-0.0904**	-0.0737	0.0248	-0.0886**
	(0.0464)	(0.0203)	(0.0413)	(0.0461)	(0.0202)	(0.0411)
χ^2	51.50	26.81	131.63	101.41	28.57	175.23
$p > \chi^2$	0.0357	0.8381	0.0000	0.0000	0.8062	0.0000
Observations	14054	14054	14054	14054	14054	14054

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Use of a count-variable regression model

To check the sensitivity of the findings to the regression model, I fit the data to a patent-level FE Poisson panel regression model using the same econometric model specifications for the forward citation count without log transformation: $FWDAll_{i,s,t}$, $FWDInt_{i,s,t}$, and $FWDExt_{i,s,t}$ as the dependent variables. Table 4.3 reports the Poisson FE regression result. Because the Poisson model drops the patents that have serial 0s in the forward citation count, the number of observations reduces from 14,054 to 12,972. The signs and statistical significance of the coefficients of the independent variables are consistent with those of the main regression results in Table 4.1.

Table 4.3: Poisson regression

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipient
PostTransfer	0.205***	0.157	0.200***	0.203***	0.119	0.200***
	(0.0561)	(0.214)	(0.0552)	(0.0599)	(0.213)	(0.0590)
FEDxPostTransfer				0.0217	0.305	-0.00342
				(0.179)	(0.452)	(0.172)
Observations	12972	3341	12748	12972	3341	12748

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As an alternative econometric model, one may want to use the conditional FE negative binomial regression model (CFNB). This model is known to fit the data better than the Poisson model when using data that has an over-dispersion problem. However, according to a simulation study by Guimaraes (2008), fitting the data to the CFNB with a T of less than 20 inflates the Type I error in testing a null hypothesis (i.e., over-rejection of the null hypothesis). Because my sample contained a maximum of 20 data points for each patent (many patents had less than 20 data points), fitting the data to CNFB ran the risk of inflating the Type I error. Due to this econometric issue, CFNB was not used for hypotheses testing.

Use of pooled DiD estimator for testing Hypothesis3

As an alternative method for testing Hypothesis 3, I use DiD estimation by reformatting the panel data into patent-level cross sectional data as employed by Galasso and Schankerman (2014). I count the number of forward citations that the patent received after its transfer until December 31, 2017, and then divide it by the number of years from the patent transfer year to 2017 to take into account the patent-level difference in the time window in counting forward citations. As with the panel regression analysis, I create three forward citation variables, $FWDPost$ (the normalized total number of forward citations that the patent received during the post-patent transfer period), $FWDPostInt$(the normalized number of forward citations made by the patent recipient during the post-patent transfer period), and $FWDPostExt$ (the normalized number of forward citations made by non-recipients during the post-patent transfer period). Then, I add 1s to them and take the natural log-transformation. The independent variable is FED.

I introduce a set of control variables to take into account the probable confounding effect of the patent-level heterogeneity. The control variables are the natural log-transformed per year number of citations that the patent received before the transfer, adding the value of 1s (*ln(PreFWD)+1*); the number of independent claims(*nClaim*); the natural log-transformed size of the patent family(*ln(Family)*); the natural log-transformed number of backward citations (*ln(BWD+1)*); whether the patent had been licensed before the patent transfer (*Licensed*)[10], and a set of dummy variables for the patent application year and the NBER

[10] One can identify universities' licensed patents by investigating patent renewal history. Under 37 CFR 1.27, a university can take the status of small entity as long as it has "not assigned, granted, conveyed,

category. Following formula describes the econometric model specification.

$$ln(PostFWDY_i + 1) = \beta_0 + \beta_1 \times FED_i + \beta_3 \times ln(PreFWD_i + 1) + \sum_k \gamma_k \times X_{i,k} \tag{4.3}$$

where $PostFWDY$ is $\{FWDPost$, $FWDPostInt$, $FWDPostExt\}$, γ_k is the coefficient of the k^{th} control variable, and X_k is the k^{th} control variable. Table 4.4 presents the regression results.

In the first through third columns, the coefficients of the FED were statistically insignificant at the 0.1 significance level. Overall, the DiD analysis with the pooled data found no evidence supporting Hypothesis 3.

Exclusion of the most active university in patent transfers

In my data, the University of California transferred the largest volume of patents to outside firms during the period of observation. To check whether my finding was driven by any peculiarities in the University of California's patent transfer activities, I exclude the university from the sample and reanalyze the data.

Table 4.5 displays the regression results. Overall, the statistical significance and signs of the coefficients of the variables of interest are consistent with those of the main regression. As a variation, I exclude the patents transferred by the University of Texas as it had the second highest number of transferred patents. Table 4.6 reports the regression result. The findings do not change substantially.

Finally, I exclude patents that were transferred either the University of California or the

or licensed, and is under no obligation under contract or law to assign, grant, convey, or license, any rights in the invention to any person, concern, or organization which would not qualify as a person, small business concern, or a nonprofit organization." Given that those with a small entity status pay discounted patent renewal fees, universities' patents that were licensed to non-small entities before the transfer must be renewed without the small-entity discount. Therefore, the patents that were renewed without the small-entity discount before the transfer can be considered as licensed patents. I also added patents that appeared in the patent assignment database as licensed patents, excluding confirmatory licenses.

Table 4.4: Pooled DiD: Testing Hypothesis 3

	Total	Recipient	NonRecipients
FED	-0.0756	-0.0310	-0.0460
	(0.0648)	(0.0312)	(0.0598)
ln(PerYear FWDAll+1)	0.581***		
	(0.0604)		
ln(PerYear FWDInt+1)		0.711***	
		(0.127)	
ln(PerYear FWDExt+1)			0.593***
			(0.0621)
ln(nClaim)	0.0836*	-0.0169*	0.0970*
	(0.0497)	(0.00938)	(0.0497)
ln(FamilySize)	0.0672*	0.000482	0.0622*
	(0.0354)	(0.0102)	(0.0353)
ln(BWD+1)	0.0599***	0.0196**	0.0455**
	(0.0195)	(0.00818)	(0.0186)
Licensed	-0.229***	-0.00827	-0.225***
	(0.0780)	(0.0160)	(0.0740)
Chemical	0.00536	0.0189	-0.0105
	(0.0844)	(0.0228)	(0.0807)
Cmp&Cmm	0.112	-0.0194	0.109
	(0.117)	(0.0257)	(0.113)
Drgs&Med	0.176	0.0176	0.172
	(0.122)	(0.0223)	(0.118)
Elec	0.0803	0.0627	0.0209
	(0.0988)	(0.0476)	(0.0841)
Mech	0.221**	0.0660*	0.158
	(0.110)	(0.0395)	(0.0998)
Constant	-0.754***	0.00393	-0.758***
	(0.227)	(0.0480)	(0.227)
R^2	0.464	0.483	0.476
Adjusted R^2	0.440	0.460	0.453
Observations	913	913	913

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

University of Texas, then re-run the regression. The results presented in Table 4.7 show consistent findings with the main regression results.

Exclusion of patent co-assignment

There could be cases where universities become the initial assignee of a patent, and the patent is later co-assigned to the university and an outside firm by legal contract. These patent co-assignments and shared ownership between universities and firms do not tech-

Table 4.5: Panel Regression excluding University of California patents

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.135***	-0.0181	0.147***	0.130**	-0.0186	0.142***
	(0.0483)	(0.0200)	(0.0442)	(0.0512)	(0.0210)	(0.0460)
FEDxPostTransfer				0.0299	0.00335	0.0354
				(0.0570)	(0.0262)	(0.0537)
Constant	0.610***	0.0356*	0.582***	-0.490***	0.0355*	-0.517***
	(0.116)	(0.0183)	(0.113)	(0.115)	(0.0183)	(0.112)
R^2	0.118	0.024	0.107	0.118	0.024	0.107
Adjusted R^2	0.115	0.021	0.104	0.115	0.021	0.104
Observations	12301	12301	12301	12301	12301	12301

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Panel Regression excluding University of Texas patents

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.150***	-0.0166	0.163***	0.151***	-0.0182	0.164***
	(0.0402)	(0.0182)	(0.0355)	(0.0440)	(0.0198)	(0.0384)
FEDxPostTransfer				-0.00689	0.00800	-0.00418
				(0.0566)	(0.0213)	(0.0560)
Constant	-0.496***	0.0452***	-0.534***	-0.496***	0.0446***	-0.533***
	(0.120)	(0.0117)	(0.119)	(0.119)	(0.0117)	(0.117)
R^2	0.120	0.022	0.110	0.120	0.022	0.110
Adjusted R^2	0.118	0.019	0.108	0.117	0.019	0.108
Observations	13071	13071	13071	13071	13071	13071

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Panel Regression excluding University of California and University of Texas patents

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.155***	-0.0167	0.168***	0.149***	-0.0168	0.161***
	(0.0464)	(0.0210)	(0.0412)	(0.0500)	(0.0220)	(0.0442)
FEDxPostTransfer				0.0374	0.000513	0.0488
				(0.0642)	(0.0297)	(0.0596)
Constant	-0.457***	0.0548***	-0.500***	-0.458***	0.0548***	-0.502***
	(0.124)	(0.0123)	(0.123)	(0.124)	(0.0123)	(0.122)
R^2	0.120	0.025	0.108	0.120	0.025	0.109
Adjusted R^2	0.117	0.022	0.106	0.117	0.022	0.106
Observations	11318	11318	11318	11318	11318	11318

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

nically fall into the practice of granting the firm the exclusive access to the university's inventions because the university still retains part of the title to the patent. To deal with these cases, I exclude patent co-assignment cases before reanalyzing the data. As a result, 39 patents (4.3%) out of the original 913 patents are dropped. The regression results with the remaining 874 patents are presented in Table 4.8. The signs and statistical significance of the coefficients of the key variables remain consistent as those in the main regression.

Table 4.8: Exclusion of Patents co-assignments

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.137***	-0.0192	0.150***	0.136***	-0.0210	0.149***
	(0.0430)	(0.0179)	(0.0389)	(0.0466)	(0.0194)	(0.0415)
FEDxPostTransfer				0.00320	0.00840	0.00342
				(0.0523)	(0.0200)	(0.0509)
Constant	0.585***	0.0288	0.561***	-0.514***	0.0283	-0.538***
	(0.111)	(0.0177)	(0.108)	(0.110)	(0.0177)	(0.107)
R^2	0.120	0.022	0.110	0.120	0.022	0.110
Adjusted R^2	0.118	0.020	0.108	0.118	0.020	0.108
Observations	13558	13558	13558	13558	13558	13558

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Taking into account the patent expiry

In the main analysis, I set the maximum period of observation to the statutory expiration date (i.e., 20 years from the patent application date). However, not all patents are fully renewed, and hence, it might not be proper to have the 20-year observations of forward citations for every patent in the sample. This could be particularly critical when considering that the expiration of patents can invite more follow-on inventions by lifting the fence around the patented invention. To address this concern, I calculate a expiration date of each patent by using the patent renewal history[11] and counting three forward citation indicators up to the newly calculated expiration date. These regression results are reported in Table 4.9. Overall, the signs and statistical significance of the coefficients of the key independent variables did not change significantly from those in the main regression analysis.

[11] Available in `https://bulkdata.uspto.gov/data/patent/maintenancefee/`.

Table 4.9: Regression taking into account the patent expiry

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.130***	-0.0185	0.142***	0.131***	-0.0205	0.143***
	(0.0423)	(0.0182)	(0.0381)	(0.0458)	(0.0198)	(0.0406)
FEDxPostTransfer				-0.00748	0.00961	-0.00675
				(0.0554)	(0.0212)	(0.0538)
Constant	0.772***	0.0102	0.757***	0.772***	0.00943	0.757***
	(0.145)	(0.0244)	(0.139)	(0.144)	(0.0243)	(0.137)
R^2	0.111	0.024	0.100	0.111	0.024	0.100
Adjusted R^2	0.108	0.021	0.098	0.108	0.021	0.098
Observations	13003	13003	13003	13003	13003	13003

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Exclusion of patents with insufficient time to observe citation data after transfer

In the main analysis, I analyzed patents that were transferred before 2014 to have at least five observations of the forward citation count for each patent. To check whether my findings were sensitive to the minimum number of observations per patent in the panel analysis, I run another regression with the patents that were transferred before January 1, 2008, so as to have at least 10 observational points per patent. The regression results presented in Table 4.10 are roughly consistent with those of the main regression.

Table 4.10: Regression with patents transferred before 2008

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.120***	-0.00635	0.133***	0.129***	-0.0143	0.148***
	(0.0359)	(0.0171)	(0.0350)	(0.0391)	(0.0187)	(0.0384)
FEDxPostTransfer				-0.0407	0.0338*	-0.0627
				(0.0550)	(0.0193)	(0.0549)
Constant	-0.541***	0.0115	-0.553***	-0.537***	0.00845	-0.547***
	(0.111)	(0.0210)	(0.108)	(0.110)	(0.0209)	(0.107)
R^2	0.141	0.018	0.133	0.141	0.019	0.133
Adjusted R^2	0.138	0.014	0.130	0.138	0.016	0.130
Observations	9346	9346	9346	9346	9346	9346

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.3 Validity of the Assumption of Patent Transfer Timing

The key assumption that enabled the causal inference in this research design is that the timing of patent transfer is exogenous. However, this assumption does not necessarily hold. For example, the timing of the patent transfer may be systematically associated with the recognized technological importance of a patented invention in the pre-transfer period. If this is the case, patent transfer timing could associate with later forward citations not by a causal impact of the patent transfer but by the selection of the patent of interest based on its technical importance.

To check the empirical validity of the assumption, I conducted a survival analysis that examines if a patent's forward citations received before the transfer associated with the hazard rate of the patent transfer. The dependent variable is the time to patent transfer in year, and the independent variable is the log-transformed forward citations that the patent received one to three years before the patent transfer, counted in the cumulative manner ($ln(FWD_{t-1}+1)$, $ln(FWD_{t-2,t-1}+1)$, and $ln(FWD_{t-3,t-2,t-1}+1)$). I used the weibull distribution for its flexibility in the distrubtional assumption. Controlling for the patent-level characteristics that were used in Table 4.4, the results in Table 4.11 indicates that the hazard rate of patent transfer is not associated with the three pre-transfer forward citation counts. This implies that there is no evidence indicating that the recognized technical importance of a patent before the transfer determines the timing of the patent transfer.

4.4.4 Alternative indicators of the Scientific Commons

In the main regression, I used patents on the outcomes of federally funded research as the proxy for invention characterized as a part of the scientific commons. The downside of this operationalization is that not all inventions originating from federally funded research are on the new scientific research outcomes.

To address this issue, I develop two alternative indicators of inventions in the scientific commons, which capture the two features of the scientific common: (1) the invention is on

Table 4.11: Survival Analysis - Timing of Patent Transfer

	Years to Transfer	Years to Transfer	Years to Transfer
$ln(FWD_{t-1}+1)$	-0.196		
	(0.131)		
$ln(FWD_{t-2,t-1}+1)$		-0.169	
		(0.117)	
$ln(FWD_{t-3,t-2,t-1}+1)$			-0.190
			(0.123)
nClaim	0.00354	0.00348	0.00348
	(0.00313)	(0.00313)	(0.00313)
ln(FamilySize)	0.0608	0.0613	0.0616
	(0.0541)	(0.0535)	(0.0533)
ln(BWD+1)	-0.0676	-0.0672	-0.0670
	(0.0539)	(0.0540)	(0.0541)
Licensed	-0.305	-0.304	-0.306
	(0.218)	(0.217)	(0.218)
Chemical	-0.0112	-0.0114	-0.0151
	(0.302)	(0.302)	(0.304)
Cmp&Cmm	-0.496	-0.495	-0.495
	(0.331)	(0.332)	(0.333)
Drgs&Med	-0.379	-0.378	-0.379
	(0.276)	(0.276)	(0.277)
Elec	-0.179	-0.179	-0.175
	(0.340)	(0.340)	(0.342)
Mech	0.434	0.436	0.443
	(0.348)	(0.349)	(0.352)
Constant	-5.649***	-5.650***	-5.647***
	(0.487)	(0.487)	(0.487)
ln_p	0.680***	0.680***	0.680***
	(0.0670)	(0.0669)	(0.0667)
Observations	846	846	846

Cluster robust standard errors in parentheses, hazard ratio reported, weibull distribution used
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

new scientific research outcome, and (2) the scientific research is funded by federal research program. The first alternative indicator is based on patent-paper pair (e.g., Murray, 2002; Murray and Stern, 2007; Thompson et al., 2018). The second indicator employs a non-patent reference (NPR) cited in the patent.

Utilizing Patent—Paper Pairs

I consider the patent that had paired scientific papers as inventions on new scientific research outcome. Patents that had paired papers on the outcome of federally funded research are considered as inventions in the scientific commons.

To identify these patents, I use the *ExPorter* database provided by the US National Institutes of Health (NIH).[12] This database contains comprehensive information about US patents and scientific papers that originated from NIH-funded research programs identified by a unique research project award number. Using this database, the patents that had paired papers on the same project number are identified. Because the *ExPorter* database provides the list of publications that are indexed by PubMed, which is a search engine for scientific publications in the life sciences and on biomedical topics, I initially select univ-transferred patents that were categorized as Drugs & Medical only. From this selected sample, I could identify 28 patents that had scientific paper pairs out of 329 Drugs & Medical patents.

Next, I add a comparison group composed of the set of patents that are not defined as scientific commons (hereafter NoSciCommon) by the two features illustrated above. These patents are not readily apparent because there is no information whether there are paper pairs for a patented invention originating from a non-NIH federally funded research project. To overcome this empirical challenge, I employ two methods for building NoSciCommon: One is to consider patented inventions that were not funded by any federal agency (including the NIH) as NoSciCommon patents. Another is considering all patents other than patents in the scientific commons as the NoSciCommon patents. I run the panel regression again for each case, using the same specifications as in the main regression, and the results are displayed in Table 4.12.

The coefficients of $NIHPub \times PostTrasfer$, which is the interaction term between $NIHPub$ (a binary variable that takes the value of 1 for patents that have scientific paper pairs on NIH funding) and $PostTransfer$ are statistically insignificant at the 0.1 significance level across all six columns. There is no evidence supporting for Hypothesis 3.

[12] `https://exporter.nih.gov/ExPORTER_Catalog.aspx`

Table 4.12: Regression with an Alternative Operationalization of Inventions on Scientific commons - With NIH Data

	Total	Recipient	NonRec'	Total	Recipient	NonRec'
PostTransfer	0.145*	-0.0215	0.163**	0.164**	-0.0130	0.175**
	(0.0767)	(0.0256)	(0.0750)	(0.0811)	(0.0284)	(0.0778)
NIHPubxPostTransfer	0.136	0.0487	0.123	0.122	0.0414	0.113
	(0.109)	(0.0618)	(0.115)	(0.110)	(0.0628)	(0.116)
Constant	-0.416***	-0.165***	-0.279**	-0.359***	-0.163***	-0.221*
	(0.111)	(0.0268)	(0.114)	(0.110)	(0.0282)	(0.113)
R^2	0.200	0.023	0.193	0.212	0.025	0.206
Adjusted R^2	0.194	0.017	0.187	0.206	0.017	0.200
Observations	4863	4863	4863	4278	4278	4278
Sample	NIH+Rest	NIH+Rest	NIH+Rest	NIH+NoFund	NIH+NoFund	NIH+NoFund

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Non-Patent Reference based indicator

Scholars in the field of bibliometrics and patent analysts have suggested that the extent to which a patent cites non-patent literature can be a rough proxy for its science link (e.g., Narin et al., 1997; Narin and Noma, 1985; Verbeek et al., 2002). The patented invention with a strong science link is likely to have drawn on new scientific knowledge. Following this idea, I consider a patent from federally funded research project with a higher proportion of NPRs in its references than a certain threshold as an invention in the scientific commons. I set the threshold on a quantile-basis. For example, if a patent had an NPR share higher than x% of the patents in the data with federal funding, that patent is classified as scientific commons. The value of x varies, and I use 50%, 75%, and 90% to check the sensitivity of the analysis results to the value of the threshold. For regression, I generate three binary variables ($NPR_x, x \in \{50, 75, 90\}$) that took the value of 1 if the patent of interest has an NPR share higher than each quantile and contains the statement of government interest, and 0 otherwise. Interaction terms between these variables and $PostTransfer$ were created ($NPR_x \times PostTransfer$). The regression results are presented in the Table 4.13.

The coefficients of $NPR_x \times PostTransfer$ are statistically insignificant at the 0.1 significance level across all the columns. Again, there is no evidence for supporting Hypothesis 3.

4.5 Discussion

In this study, I explored how granting a firm the exclusive right to use the university's invention does affect development of follow-on inventions.

The prior literature on the broad discussion around the necessity for a formal institution that enables exclusive use of university inventions derive first two hypotheses: granting a firm the exclusive access to a university's invention promotes the recipient working toward follow-on inventions (H1), and also encourages non-recipients' to work on subsequent inventions (H2). The studies on the concerns about the consequence of the privatization of scientific commons derive the third hypothesis: the size of the positive impact of giving the exclusive right to use a university's invention to an outside firm on the rate of follow-on invention is marginalized when the invention is featured as a part of the scientific commons (H3).

I empirically tested the three hypotheses by considering patent ownership transfers from universities to firms as a way of granting a firm the exclusive access to a university's inventions. I operationalized the universities' inventions in the scientific commons in three ways: patents on the outcomes of publicly funded research, patents that have scientific paper pairs with federal sponsorship, and patents that have a strong science link measured by NPR with federal sponsorship. My data consisted of 913 US granted patents that were transferred from 107 intensive research universities to firms in the United States between 2000 and 2013.

My analysis utilizing variations in the timing of the patent transfer yielded several interesting findings. First, there was no evidence showing that conferring exclusive access to a university's inventions to an outside firm through patent transfer affects the recipient's innovative activities around the university's invention. However, I did find robust evidence showing that the rate of non-recipient subsequent inventions increased after a patent transfer.

These findings imply that granting a firm the exclusive access to a university's inventions positively affects the rate of follow-on invention, realized through promoting innovative activities of the non-recipients around the university's inventions. The studies by Drivas et al. (2017) and Thompson et al. (2018) drew the same conclusion by analyzing exclusive patent license data of University of California.

The positive externality can be explained by following two. One is as an indicator of increasingly invigorated innovative activities around the transferred university's patented inventions. Another possibility is as the trigger of the innovative activities around the university's invention. Acquisition of a university's patent by an outside firm might encourage other entities to dive into developing and preempting relevant inventions in the belief that the university's transfer of the patent may be related to future technological opportunities.

If any of these mechanisms worked, why is there no evidence showing an increase in the rate of a recipient's follow-on invention after the patent transfer? I suggest two hypothetical explanations, which requires empirical tests in the future.

One is self-selection. Those who are not capable of developing inventions relative to the university's patent or are not willing to develop such follow-on inventions may seek to obtain the university's invention from the beginning. A study by Kelley (2011) suggested that firms use the acquisition of external patents to equip themselves with intellectual property assets that they were not capable of internal development.

Another is the incentive for developing alternative inventions. After acquiring exclusive access to a university's patented invention, the recipient may have become to focus on making peripheral technologies that are necessary for commercializing the university's invention they obtained. This can include reconfiguration of the technical specifications or technological performance improvements to the original inventions. It may also be the case that a firm acquires a university's inventions not to initiate a new R&D project but to solve the technical issues of an ongoing project (Cohen et al., 2002). The outcomes of these efforts are unlikely to end up with new inventions that are sufficiently novel to be patented.

On the other hand, those who did not have the accessibility to the university's inventions but are interested in capturing the relevant technological opportunities must invent around or develop substantially improved inventions than the university's invention in question in order not to infringe upon the existing patents. This could have driven the nonrecipients' "patented" inventions around the university's inventions.

Surprisingly, my analysis found no evidence showing that granting a firm the university's inventions in scientific commons marginalizes its positive effect on the development of follow-on inventions. Instead, doing so appeared to promote non-recipients' follow-on inventions.

Based on this analysis result, one might claim that we need to promote a university's practice of granting a firm the exclusive access to its inventions in the scientific commons. However, my findings should not be interpreted in this way. First, my findings could be the result of the universities' careful selection of patents for transfer or the existence of an institutionalized screening process to ensure that the benefit of enabling exclusive access to the university's invention exceeds its probable social cost. In the United States, such a screening process is already institutionalized. By law, universities must report the transfer of patent ownership and obtain approval from the federal funding agencies if the patents are based on the outcomes of federally funded research. It is essential to take into account how such institutions work well when discussing its social welfare consequence. Second, this finding should be interpreted restrictively as the impact of the privatization of the university's inventions in the scientific commons on the rate of follow-on inventions rather than on the entire innovation or the social welfare. Encouraging follow-on invention is not necessarily socially desirable, and even doing so may drive the duplication of R&D (e.g., Gilbert and Newbery, 1982; Wright, 1983; Jones and Williams, 2000). Third, this finding may hold only for the universities' "patented inventions", not necessarily for the universities' entire knowledge. As discussed in Section 2, once universities patent on inventions containing the scientific research outcome, doing so immediately privatize the probable scientific commons. Hence, the transfer of patented inventions in scientific commons to private entities may not generate or aggravate the "privatization of scientific common" effect. Empirical analysis on how the privatization of scientific commons that are not patented affects the development of follow-on inventions is necessary for more conclusive understanding.

4.6 Contribution and Limitations

The contribution of this study is twofold. First, the present research advances the long-standing debate on the consequences of granting a firm the exclusive access to a university's inventions for innovation. My study sheds the first empirical light on the impact to the rate of follow-on invention of the transfer of patents to inventions that are featured as part of the scientific commons on the rate of follow-on inventions. Contrary to such general concern, conferring a firm the exclusive access to a university's inventions in the scientific commons patent transfer promoted the development by non-recipients of follow-on inventions. This study also empirically contributes to expanding the recent scholarly efforts toward elucidating how a university's exclusive patent licensing affects the rate of follow-on innovation (Drivas et al., 2017; Thompson et al., 2018). The contribution of the present study lies in the fact that I directly examined the impact of privatization of universities' inventions in the scientific commons and investigated the impact on the rate of follow-on inventions more comprehensively by analyzing the 107 research-intensive US universities' patent transfer data than using a few selected universities' cases of exclusive patent licensing.

Second, this study contributes to the literature on the NIS by emphasizing a less-explored role of universities in the NIS— patent supplier in the market for patents. Prior literature on the NIS describes universities as the locus of knowledge creation and flow (Mowery et al., 2004; Youtie and Shapira, 2008). My study points to this other role of universities, which may shape the dynamics of innovation differently from the conventional ways. Given that a patent confers the legal right for the patent owner to exclude others from using the patented invention, universities as patent suppliers need to be distinctively understood separate from the conventional view of the roles and positions of universities in the innovation system. My study hints by showing that the observed effect of the university's patent transfer on the follow-on inventions is difficult to be explained by the technology transfer effect alone. If the university's patent transfer served a channel for knowledge diffusion and technology transfer, the patent recipient' innovative activities around the transferred patents should have been prompted. Yet, my analysis found no evidence. This may indicate that it is necessary to explore further in depth how universities play in the market for patents and the consequence of their patent trading activities for innovation, with the distinct perspective from the conventional role of universities as the central innovative players for technology transfer.

The present study has weaknesses that may become opportunities for future research. The empirical findings were based on the US case because the analysis was enabled by data on US patents that were transferred by US universities. I hope future studies to add more evidence from the case of non-US countries.

As an empirical strategy, I used the number of patent forward citations as the proxy for the rate of follow-on inventions of the focal patented invention. However, this empirical strategy is imperfect because not all inventions are patented (Cohen et al., 2000; Moser, 2012), nor are all follow-on inventions patented. Hence, my use of the patent forward citation captures only part of the entirety of follow-on inventions.

There are various reasons for universities to transfer their patents. They may transfer ownership of patents to their spin-offs or sell the patents to firms through typical market transactions. Although it is likely true that the different reasons for patent ownership transfer may generate heterogeneous dynamics regarding its impact on the rate of follow-on inventions, my study did not take into account this probable heterogeneity for the data limitation.

I hope my work becomes a stepping stone for future studies to explore more about universities' patent transfer activities and the implications of those transfer for innovation.

Table 4.13: Regression with an Alternative Operationalization of Inventions on Scientific commons - With NPR citation data

	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients	Total	Recipient	NonRecipients
PostTransfer	0.129***	-0.0211	0.142***	0.136***	-0.0166	0.147***	0.134***	-0.0178	0.146***
	(0.0431)	(0.0179)	(0.0384)	(0.0427)	(0.0178)	(0.0381)	(0.0421)	(0.0175)	(0.0381)
NPR_{50}xPostTransfer	0.0370	0.0289	0.0314						
	(0.0752)	(0.0247)	(0.0738)						
NPR_{75}xPostTransfer				-0.0407	-0.0182	-0.0209			
				(0.0735)	(0.0171)	(0.0761)			
NPR_{90}xPostTransfer							-0.00689	-0.00520	0.00222
							(0.0870)	(0.0193)	(0.0890)
Constant	-0.525***	0.0265	-0.547***	-0.523***	0.0275	-0.545***	-0.523***	0.0273	-0.546***
	(0.111)	(0.0174)	(0.108)	(0.111)	(0.0177)	(0.108)	(0.112)	(0.0176)	(0.108)
R^2	0.118	0.022	0.109	0.118	0.021	0.109	0.118	0.021	0.109
Adjusted R^2	0.116	0.019	0.107	0.116	0.019	0.107	0.116	0.019	0.106
Observations	14054	14054	14054	14054	14054	14054	14054	14054	14054

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 5
CONCLUSION

5.1 Summary

The present dissertation has explored how the market for patents shapes innovation. In the first essay, I examined how a firm's purchase of a patent affects other firms' development of technologies relevant to that patent. In particular, this study focused on examining the negative externality of a firm's patent purchase to the market competitor's innovative activities when the patent is crucial for the rival firm's market operations. A three-firm model in this study predicted that when a firm purchases a patent related to crucial technological input for their market competitor's production, it negatively affects the rival's production level and the development of technologies relevant to the patent of interest. This is because after the firm purchases the patent, it becomes capable of manipulating the rival's market operations by leveraging the ex-post patent holdup risk to the rival firm, and this risk deters the rival firm from developing the relevant technology.

I empirically tested the derived prediction by analyzing the case of Nortel's patent auction in 2011. As part of its bankruptcy, the Canadian telecommunication equipment company Nortel liquidated its communication technology patent portfolio through a patent auction, where some global smartphone manufacturers and technology firms participated in the bidding. The fact that telecommunication technology is a crucial input for making smartphones, and that the participants at this auction were in competition with each other in the smartphone market, made this a good case to use for my analysis. According to the model prediction, the auction-winning firms that could acquire the Nortel patents were expected to divert the auction-losing firms' development of technologies relevant to the Nortel patents. My analysis, using a difference-in-difference (DiD) approach, found strong evidence supporting this prediction. The auction-losing firms became less active in developing telecommunication technologies that had direct technological links to the Nortel patents after other firms acquired them at the auction. Interestingly, this impact existed for a short-term. The existing literature and my additional analysis suggested that, through post-auction strategy, the auction-losing firms became to cope with the probable ex-post patent holdup risk raised by the auction-winning firms' acquisition of the Nortel patents.

Essay 2 focused on the institutional tension between patent and antitrust law. In this study, I examined how antitrust regulation of a firm's patent consolidation impacts the rate of follow-on innovation. Toward this end, I built an analytical model to illustrate how a firm's patent consolidation and consequential formation of patent monopolies affect the development of follow-on innovation. The model predicted that when a firm consolidates patents around a technology that is substitute for the technology they already possess, it discourages development of follow-on innovations by market competitors and simultaneously removes the incentive for the firm that purchased the patent to develop any follow-on innovations. In this case, authority's regulation of patent monopoly formation through prevention of patent consolidation was expected to promote market competitors' follow-on innovation activities.

For the empirical test, I analyzed the case of the US Department of Justice's (DoJ) partial regulation of CPTN Holdings' (a consortium of Microsoft, Oracle, EMC, and Apple) consolidation of Novell's software patents in 2011, considering the patented inventions as the outcome of the innovative activities. Most of Novell's patents had been shared with the Linux community through the Open Invention Network (OIN), which was jointly established by its six member companies (Novell, IBM, Red Hat, Sony, Philips, and NEC) to protect the open-source software community from software patent infringement disputes through pooling the patents. In 2010, Novell tried to sell its software patents to CPTN Holdings, but the US DoJ intervened in the deal because CPTN's member companies' consolidation of the Novell patents could be detrimental to competition in the software market.

The intervention was a partial regulation of patent transfer whereby Novell had to retain the patents that were originally planned to be consolidated by Microsoft. However, the rest of the patents could be successfully aggregated by the other three member companies of CPTN. I capitalized on this partial regulation for my analysis. Using data on the Novell patents that were the subject of this transfer deal, I compared the number of follow-on inventions created for the regulated patents and those created for the transferred patents after the DoJ's intervention. Because OIN member companies were in market competition with the patent consolidating firms in the software market, my theoretical model expected that the OIN members would develop more follow-on inventions for the regulated patents than for the transferred patents. My analysis using DiD and a synthetic control approach found robust evidence supporting this prediction.

In the third essay, I moved the lens to a university's patent transfer activity. In particular, I focused on whether granting an outside firm exclusive access to a university's inventions through patent ownership transfer promotes or discourages innovative activities around the focal university's patents. The literature on the necessity for formal institutions that enable exclusive access to a university's inventions expects that granting firms the exclusive access to a university's inventions will promote the innovative activities around the university's invention by both the recipient of exclusive access and the non-recipients (H1, H2). The scholarly discussion of the privatization of university inventions in the scientific commons suggested that conferring a firm the exclusive access to a university's inventions in scientific commons marginalizes its probable positive impact on the rate of follow-on inventions (H3).

I empirically tested the three derived hypotheses by analyzing the panel data of US patents that were transferred from 107 research-intensive US universities to firms between 2000 and 2013. I operationalized inventions in the scientific commons with patents on federally funded research or patents that had a strong science link, such as scientific paper pairs or extensive citation to the non-patent references. My analysis found no evidence showing that the recipient's follow-on invention development was encouraged after the university transferred patent ownership to the firm. In contrast, it seemed to promote the development of follow-on inventions by the non-recipients of the university's patent. Interestingly, there was no evidence showing that a university's transfer of patents that are featured as the scientific commons marginalized this positive impact. From the findings, I concluded that granting a firm the exclusive access to a university's inventions through patent transfer seems to encourage non-recipients' subsequent innovative activities through the signal mechanism. The patent transfer may indicate the emergence of technological opportunity, which encourages other innovators to jump into developing technologies around the university's transferred patents.

5.2 Conclusion and Policy Implication

5.2.1 Conclusion

The three essays jointly draw the following conclusions. First, the market for patents should not be considered merely a part of the market for technology. As the first essay showed, firms have economic incentives to purchase external patents if they are critical for a rival's market operations. Doing so gives strategic benefits in market competition to the patent purchasing firm by allowing it to leverage a market rival's patent holdup risk. In this case, the firm's purchase of a patent imposes a greater cost of innovation on the rival firm. Although patent transfers can be an alternative method of transferring technology or be the result of technology transactions, we need to recognize that the market for patents has a distinctive nature separate from the market for technology.

The findings in the second essay reached the same conclusion but then went further to show that when a firm consolidates substituting patents for what it already owns, an antitrust issue can arise for the purchasing firm at the same time as the purchase brings negative externality to market competitors' follow-on innovative activities. However, this consequence does not occur if the subject of the transaction is a technological idea. This implication could be particularly important for policymakers who seek to encourage the trading of patent ownership in the belief that an active market for patents will encourage innovation by promoting the transfer of technology.

Second, there is an immediate call for cross-domain policy discourse and interdisciplinary scholarly work regarding how the market for patents affects social welfare. As the second essay explored, patent transfers could raise issues in the area of antitrust as well as in the innovation policy domain. Although Essay 2 contributed to explorations of how the market for patents could be particularly pertinent to antitrust and innovation policy, an area requiring further comprehensive exploration is whether and how the patent market might shape various dimensions of social welfare.

Third, when it comes to understanding the consequences of patent protection for innovation, an important factor to consider is who owns which patents rather than solely emphasizing whether patent protection of technological ideas promotes or discourages innovation. The prior discussion was focused on the tension between the opposite effects that patent protection has on innovation: on the one hand, the patent system incentivizes innovation by rewarding innovators with a temporal monopoly on a technological idea, but on the other hand, it can restrict knowledge diffusion and bar access to inputs that would encourage further innovation. The present dissertation extends this conventional understanding by showing that the consequences of patent protection for innovation may depend on the ownership of the patent—in other words, who owns which patents. The first essay suggests that if a patent is owned by those who have a strong incentive to use the patent strategically against rival firms, the existence of the patent may work toward distorting a rival firm's innovative activities.

The second essay concluded that if a patent is owned by a patent monopolist, the existence of the patent may discourage market competition and follow-on innovation by market competitors. This conditional consequence to innovation from the existence of patents is also supported by the third essay. Patent ownership transfer from a university to a firm could be a indicator of emerging technological opportunity that induces more follow-on innovation by non-recipients of exclusive access to a university's inventions.

5.2.2 Policy Implications

The three essays of this dissertation point to the presence of **externality** as the key feature of the market for patents. The existence of externality highlights why the market for patents needs to be subject to policy discussion about its consequences to social welfare.

In the remainder of this section, I describe the policy implications of this dissertation while providing useful actions that policymakers can use when formulating measures for promoting technological innovation, when the subject comes to the market for patents.

(1) Determine which patent transfers will bring externality

First of all, it is necessary to investigate which patent transfers might impose which type of externality upon whom. I suggest that governmental authorities should first distinguish whether the patent transfer in question is for a technology transfer or for the transfer of the patent exclusion right. If the latter is the case, the patent transfer can generate the negative externality issues already discussed. Answering the following two questions can be helpful in this regard:

- Does the purchasing firm have more incentive than the seller does to use the patent to impose a greater level of ex-post patent holdup risk to other firms?
- Does the patent purchasing firm possess any patents on technologies that are substitutable for the patent in question?

Regarding the probable positive externality of a patent transfer influencing follow-on innovative activities, the regulatory authority may need to ascertain whether the underlying technological idea in the transferred patent is part of emerging technological opportunities.

If this question is answered positively, the authority can expect the patent transfer to have a positive externality on follow-on innovative activities among even those who did not acquire the patent.

Note that both negative and positive externalities can occur with the same patent transfer. For example, a firm may purchase patents that are part of emerging technological opportunities, while at the same time, such patents could be critical for some of its market rival's operations. In this case, the net effect of the patent transfer becomes the subject of empirical analysis.

(2) Investigate who the patent seller is and which entities would be affected by the externality

Is the governmental authority's intervention in a patent transfer always desirable if the patent transfer is likely to impose a negative externality on others' innovative activities?

The answer is dependent upon who the patent seller is and who might suffer from a negative externality. The first essay showed that once a firm purchases a patent that is crucial for rival firms' market operations, the focal firm's patent acquisition can deter competitors' innovative activities around the patent, but only for a short time. The damping effect is short-term because rival firms may be able to equip themselves to mitigate the patent transfer-induced holdup risk. In that case, the governmental authority's intervention in the patent transfer may not be necessary.

However, if rival firms are not capable of building an adequate coping strategy (e.g., as with small businesses), the impact of negative externality could persist long enough to harm the business. In this case, the governmental authority may need to consider a proper policy instrument to allow for intervention in the patent transfer, either directly or indirectly.

It is also important to take into account who the patent seller is. When the patent seller is a failing firm, restricting its patent sale because of concerns about negative externality to other firms' innovative activities implicitly imposes an exit cost on the patent owner. The restricted patent liquidation effectively weakens the patent's enforceability and erodes patent-induced ex-ante incentive for innovation. Furthermore, the restricted patent's enforceability may induce less-efficient players to enter the market, which in turn might be harmful to consumer welfare (Gilbert and Shapiro, 1996).

In contrast, it is also possible that proper restriction of a patent transfer and the opportunistic patent enforcement that would occur thereafter can help innovation, as hinted by the literature on compulsory licensing (e.g., Moser and Voena, 2012; Tandon, 1982).

Such probable opposite consequences of governmental restriction on patent transfer for the protection of innovation is not different from the conventional debate about whether the patent system properly incentivizes or hampers innovation.

One can consider the governmental purchase of a failing firm's patents to be an alternative policy instrument, which was originally discussed by Kremer (1998). For example, as studied in Essay 2, when a failing firm tries to sell its patents, if it is expected that the patent buyer would then have an excessive concentration of existing patents on an upstream technology, the government could consider acquiring the patent by itself as a possible intervention option. In doing so, the patent seller would still obtain the salvage value of the patent, to some extent (i.e., the ex-ante value of the patent), while the government would be able to ensure that the patent would not be used to discourage innovation or market competition. Later, the government can place the patent in the public domain so that anyone can use the invention.

In Essay 3, I showed that a university's patent ownership transfer to a firm encourages the purchaser's rival firms to conduct innovative activities related to the patent. I suggested that this was because the university's patent transfer may be indicative for an emerging technological opportunity to the rest of the innovating firms in the field and, thus, promote follow-on innovative activities by them. If so, should the authorities encourage patent transfers at universities to prompt innovation? One cannot draw this conclusion. The positive externality was only for "follow-on innovation" as opposed to all possible innovative activities. If the university's patent transfer results in overinvestment in follow-on innovations, it could lead to suboptimal resource allocations for R&D from a societal viewpoint. Accordingly, policymakers need to determine from the start whether the positive externality for follow-on innovation of a patent transfer is socially desirable.

Note that my study did not examine the situation where a firm acquires the patent on a technology that is complementary to technologies the firm already owns. Given that acquiring complementary technological assets enhances an innovator's appropriability (Teece, 1986), while also becoming a crucial resource for further innovation, how the patent transfer for complementary technology acquisition affects innovation will be an intriguing future research question. The combination of my study's findings and the existing literature leads me to suggest that a patent purchase made by a firm for the acquisition of complementary patented technology will bring somewhat less obvious effects on innovation. The patent transfer may promote the patent-purchasing firm's innovative activities while making rival firms less active in developing technologies relevant to the transferred patent, if the patent is crucial for rival firms' operations.

All the suggestions I have made above are inconclusive initial sketches. Nevertheless, I believe that this discussion could serve as a stepping stone for later research further exploring how the market for patents shapes innovation and social welfare.

Appendices

APPENDIX A

ROBUSTNESS CHECK (CHAPTER 3)

Use of count-variable models

The nature of the dependent variable is count variable. Although the natural log-transformation of the count variables is widely used in regression analysis, it can be problematic when dealing with the zero-observations (i.e., adding 1s). In this case, using Poisson or Negative binomial model is preferred (Ohara and Kotze, 2010). To check whether my findings are robust to the count-variable regression models, I run the Poisson- and negative binomial models[1] while using the four forward-citation variables without log-transformation. Table A.1 and A.2 report the regression results. The signs and statistical significance of the coefficients of the **regulated** are largely consistent with the main regression result.

Placebo Test

Could the present study's findings be a result of coincidence? To rule out this possibility, I conducted a placebo-test. I posited that the Novell's patents sale and DoJ's intervention into it occurred on April 20, 2008 (placebo intervention date). Then, I counted the four forward citation variables beginning from the placebo intervention date and up until April 20, 2011 (3-year window). As a control variable, I counted the number of forward citations accrued by the two groups of Novell patents from April 20, 2005, to April 20, 2008. If my finding is specific to the actual timing of the DoJ's intervention, the number of follow-on inventions for the regulated and transferred patents after the placebo intervention date is unlikely to be different in the given time window. Table A.3 reports the regression result of this placebo test.

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[1] I used generalized linear model with family(poisson) and family(negative binomial) respectively employing the robust standard error to avoid issue of misspecification of the distribution

Table A.1: Poisson Regression

	PostCiteOIN	PostCiteCPTN	PostCiteRem	PostCiteAll
Regulated	**0.873*****	0.300	0.154	0.159
	(0.297)	(0.261)	(0.160)	(0.142)
PreCiteOIN	0.185***			
	(0.0392)			
PreCiteCPTN		0.124***		
		(0.0140)		
PreCiteRem			0.0387***	
			(0.00335)	
PreCiteAll				0.0365***
				(0.00280)
nClaim	-0.000362	0.0107	0.0110*	0.00881*
	(0.00742)	(0.00979)	(0.00576)	(0.00518)
DoJConcern	0.0357	-0.337*	-0.108	-0.225
	(0.302)	(0.204)	(0.164)	(0.152)
CiteOINPat	0.454	-0.0501	0.00303	0.132
	(0.487)	(0.224)	(0.204)	(0.185)
CiteMSPat	-0.0806	0.0129	-0.00932	0.00630
	(0.319)	(0.203)	(0.143)	(0.127)
EuroFam	-0.699	-0.118	-0.760***	-0.725***
	(0.554)	(0.295)	(0.292)	(0.236)
Constant	-29.11	-31.76*	-0.303	-0.433
	(.)	(17.50)	(0.976)	(0.854)
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes
Observations	432	432	432	432

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The coefficients of **regulated** are statistically insignificant at the 0.1 significance level across all the columns. Specifically, the statistical significance of coefficient of **regulated** on **ln(PostCiteOIN+1)** disappears. This indicates that my original findings are specific to the actual timing of the DoJ's intervention.

Sub-Sample Regression

Could my findings be simply driven by the peculiar characteristics of patents that were acquired by a certain CPTN member company? To rule out this possibility, I constructed

Table A.2: Negative Binomial Regression

	PostCiteOIN	PostCiteCPTN	PostCiteRem	PostCiteAll
Regulated	**0.476****	0.101	0.163	0.178
	(0.231)	(0.213)	(0.126)	(0.115)
PreCiteOIN	0.339***			
	(0.0732)			
PreCiteCPTN		0.221***		
		(0.0601)		
PreCiteRem			0.0808***	
			(0.00927)	
PreCiteAll				0.0662***
				(0.00634)
nClaim	0.00481	0.0102	0.0145***	0.0132***
	(0.00839)	(0.00737)	(0.00407)	(0.00396)
DoJConcern	0.228	-0.614***	-0.142	-0.237*
	(0.253)	(0.188)	(0.134)	(0.122)
CiteOINPat	0.441	0.0583	-0.125	0.00494
	(0.323)	(0.207)	(0.133)	(0.117)
CiteMSPat	-0.111	0.291	0.0542	0.0922
	(0.238)	(0.182)	(0.118)	(0.107)
EuroFam	-0.560	-0.00309	-0.201	-0.368**
	(0.368)	(0.266)	(0.207)	(0.175)
Constant	-29.15***	-30.10	-1.378***	-1.291**
	(1.581)	(.)	(0.511)	(0.512)
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yesb	Yes	Yes	Yes
Observations	432	432	432	432

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

three sets of patent sub-samples by excluding patents that were acquired by Oracle, EMC, and Apple respectively at a time, and ran the regression for each sub-sample. Table A.4 to Table A.6 present the regression results. The coefficient of the **regulated** stays positive and statistically significant at least the 0.1 significance level.

Table A.3: Placebo Test

	ln(PostCiteOIN+1)	ln(PostCiteBuyer+1)	ln(PostCiteRem+1)	ln(PostCiteAll+1)
Regulated	-0.0853	-0.0255	0.0330	-0.0157
	(0.0673)	(0.0818)	(0.0979)	(0.0992)
ln(PreCiteOIN+1)	0.442***			
	(0.0733)			
ln(PreCiteCPTN+1)		0.372***		
		(0.0513)		
ln(PreCiteRem+1)			0.841***	
			(0.0378)	
ln(PreCiteAll+1)			0.776***	
				(0.0410)
nClaim	0.00528**	0.00167	0.00462	0.00399
	(0.00236)	(0.00330)	(0.00314)	(0.00334)
DoJConcern	0.0167	-0.0658	-0.170*	-0.0976
	(0.0742)	(0.0870)	(0.0924)	(0.0919)
CiteOINPat	0.0878	-0.0733	-0.238**	-0.214**
	(0.0668)	(0.0850)	(0.0928)	(0.0975)
CiteMSPat	0.0108	0.0742	0.0864	0.122
	(0.0623)	(0.0796)	(0.0871)	(0.0870)
EuroFam	-0.110	0.00315	0.0475	-0.0302
	(0.0838)	(0.102)	(0.123)	(0.116)
Constant	0.821***	-0.418	0.247	0.968***
	(0.235)	(0.526)	(0.243)	(0.236)
R^2	0.275	0.345	0.655	0.631
Adjusted R^2	0.219	0.294	0.628	0.602
Observations	346	346	346	346

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Regression excluding Oracle-Purchased Patents

	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteRem+1)	ln(PostCiteAll+1)
Regulated	**0.146****	-0.0152	0.000339	-0.0133
	(0.0663)	(0.0741)	(0.0961)	(0.0937)
ln(PreCiteOIN+1)	0.329***			
	(0.0718)			
ln(PreCiteCPTN+1)		0.643***		
		(0.0755)		
ln(PreCiteRem+1)			0.921***	
			(0.0424)	
ln(PreCiteAll+1)				0.927***
				(0.0440)
nClaim	-0.00145	0.00361	0.00249	0.00217
	(0.00218)	(0.00333)	(0.00345)	(0.00341)
DoJConcern	0.0228	-0.124*	-0.0441	-0.0767
	(0.0732)	(0.0740)	(0.105)	(0.101)
CiteOINPat	0.0874	0.0269	0.0566	0.105
	(0.0654)	(0.0758)	(0.107)	(0.102)
CiteMSPat	-0.0435	0.0791	0.0121	0.0147
	(0.0646)	(0.0700)	(0.0884)	(0.0862)
EuroFam	-0.0906	-0.0126	-0.0934	-0.0873
	(0.0939)	(0.0786)	(0.146)	(0.135)
Constant	-0.121	-0.308	0.268	0.309
	(0.162)	(0.246)	(0.283)	(0.269)
R^2	0.195	0.412	0.682	0.676
Adjusted R^2	0.112	0.352	0.650	0.643
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes
Observations	335	335	335	335

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Regression excluding EMC-Purchased Patents

	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteRem+1)	ln(PostCiteAll+1)
Regulated	**0.201*****	0.0233	0.176*	0.211**
	(0.0673)	(0.0719)	(0.103)	(0.0984)
ln(PreCiteOIN+1)	0.344***			
	(0.0547)			
ln(PreCiteCPTN+1)		0.603***		
		(0.0682)		
ln(PreCiteRem+1)			0.928***	
			(0.0450)	
ln(PreCiteAll+1)				0.951***
				(0.0433)
nClaim	-0.000353	0.00416	0.00192	0.00261
	(0.00223)	(0.00349)	(0.00384)	(0.00373)
DoJConcern	0.0109	-0.123	0.139	0.0442
	(0.0691)	(0.0767)	(0.105)	(0.101)
CiteOINPat	0.137**	-0.0197	-0.0856	-0.0655
	(0.0563)	(0.0855)	(0.108)	(0.110)
CiteMSPat	-0.0228	0.0104	0.0496	-0.0147
	(0.0611)	(0.0718)	(0.0872)	(0.0858)
EuroFam	-0.0423	-0.0575	-0.0958	-0.119
	(0.0799)	(0.0844)	(0.123)	(0.127)
Constant	-0.251	-0.540**	0.382	0.0734
	(0.164)	(0.265)	(0.261)	(0.269)
R^2	0.257	0.454	0.668	0.670
Adjusted R^2	0.178	0.396	0.633	0.634
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes
Observations	323	323	323	323

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Regression excluding Apple-Purchased Patents

	ln(PostCiteOIN+1)	ln(PostCiteCPTN+1)	ln(PostCiteRem+1)	ln(PostCiteAll+1)
Regulated	**0.121***	0.0197	0.0901	0.0589
	(0.0668)	(0.0757)	(0.100)	(0.0952)
ln(PreCiteOIN+1)	0.357***			
	(0.0596)			
ln(PreCiteCPTN+1)		0.611***		
		(0.0663)		
ln(PreCiteRem+1)			0.871***	
			(0.0462)	
ln(PreCiteAll+1)				0.883***
				(0.0435)
nClaim	-0.00102	0.000921	0.00269	0.00158
	(0.00231)	(0.00365)	(0.00359)	(0.00347)
DoJConcern	-0.00453	-0.109	0.0328	-0.0657
	(0.0656)	(0.0751)	(0.105)	(0.0982)
CiteOINPat	0.128*	0.000973	0.00817	-0.00451
	(0.0694)	(0.0795)	(0.110)	(0.101)
CiteMSPat	-0.0305	-0.0164	0.0198	0.00347
	(0.0642)	(0.0686)	(0.0916)	(0.0853)
EuroFam	-0.00649	0.0309	-0.0223	-0.0569
	(0.0761)	(0.0871)	(0.126)	(0.121)
Constant	-0.407*	-0.590*	0.213	-0.102
	(0.239)	(0.326)	(0.283)	(0.319)
R^2	0.251	0.446	0.647	0.670
Adjusted R^2	0.174	0.389	0.611	0.636
AppYrFE	Yes	Yes	Yes	Yes
TechFE	Yes	Yes	Yes	Yes
Observations	332	332	332	332

Robust standard errors in parentheses, Placebo regulation date: April 20, 2008

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX B

OVERVIEW OF SYNTHETIC CONTROL METHOD (CHAPTER 3)

Abadie and Gardeazabal(2003) and Abadie et al.(2010) pioneered the SC method. The key principle of the SC is creating a synthetic counter-factual of the treatment-group by mixing individual units from the pool of control units (i.e., donor pool). The mix of control units becomes the SC unit. In this section, I briefly explain how the SC method works by reviewing two seminal works on the subject by Abadie et al. (2010) and Kreif et al. (2016).

Abadie et al.(2010) describes how to apply the SC method when there is one treated unit and multiple control units.

Consider that there are $J + 1$ units. The first unit is the one that is exposed to the treatment of interest (i.e., the DoJ's intervention into the patents transfer in the present study) at $T_0 + 1$ whereas the rest of them (from the unit 2 to $J + 1$) have not been assigned to the treatment of interest during the period of observation. The outcome of each unit is observed from time $t = 1$ to $t = T$ (where $T > T_0$). The outcome of each unit at time t can be modeled into:

$$Y_{jt} = Y_{jt}^N + \alpha_{jt} D_{jt} \tag{B.1}$$

where Y_{jt}^N is the treatment-free outcome of the jth unit at time t, α_{jt} is the treatment effect, and D_{jt} is the binary variable that takes the value of 1 if unit j is assigned to the treatment at time t where $t \in [T_0 + 1, ..., T]$.

Y_{jt}^N is a linear combination of the time fixed effect (δ_t), a vector of the time-invariant unobserved factor(s) (μ_j), and the time-invariant observed factor(s) (Z_j).

$$Y_{jt}^N = \delta_t + \lambda_t \mu_j + \theta_t Z_j + \epsilon_{jt} \tag{B.2}$$

Now, consider the treated unit. Since Y_{1t}^N is unobservable, the SC method instead uses a weighted sum of the post-treatment outcomes of the units in the donor pool ($\hat{Y_{1t}^N}$) as the "synthesized counter-factual" of the treated unit.

The weights(W) are chosen so that the weighted pre-treatment outcome as well as other selected covariates of untreated units are as close as possible to those of the treated unit. More formally, $\hat{Y_{1t}^N} = \sum_{j=2}^{J+1} w_j Y_{jt}$, where $\sum_{j=2}^{J+1} w_j = 1$. W minimizes the loss function as follow:

$$\min_{W} \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{B.3}$$

where X_1 is the vector of covariates including the pre-treatment outcome of the treated unit, X_0 is the vector of the covariates of the untreated units, V is the matrix that specifies the relative importance of the covariates and the pre-treatment outcome.

The treatment effect is estimated by $\hat{\alpha_{1t}} = Y_{1t} - \hat{Y_{1t}^N}$. Abadie et al.(2010) showed that $\hat{\alpha_{1t}}$ is an unbiased estimator of α_{1t} if the covariates and pre-treatment outcome of the synthetic control equal to those of the treated units.

Kreif et al.(2016) suggests an extended version of the SC method for cases where multiple treated and control units exist. The key idea is to aggregate treated units into a single aggregated treated unit; this is accomplished by taking the weighted average of the characteristics of all the treated units. Then, the SC of the aggregated treated unit is constructed by the same procedure used by Abadie et al. (2010).

In sum, one can make the aggregated treated unit by taking the arithmetic average of each treated unit's pre-treatment period outcomes and the selected covariates. Then, the SC is constructed by finding W, which minimizes the discrepancy between the characteristics of the aggregated treated unit and the control units.

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